*** By Savita ***

Zomato Analytics - Exploratory Data Analysis

Objective

Perform a thorough Exploratory Data Analysis (EDA) to uncover insights into restaurant performance, customer preferences, and dining trends. Identify actionable patterns in restaurant ratings, customer feedback, pricing, and other crucial factors to guide informed business decisions.

Dataset Of Zomato

The dataset provides detailed information about restaurants listed on **Zomato**, including:

1. Restaurant Details

- **Names**, **cuisines served**, **locations**, and **operating areas** of restaurants.

2. Customer Feedback

- **Ratings**, **votes**, and **reviews** reflecting customer preferences and satisfaction.

3. Pricing Information

- **Average cost for two people** and related **pricing details** to understand affordability trends.

4. Geographical Insights

- Data segregated by **regions, cities, and countries**, helping analyze location-based patterns.

5. Categorical Details

- **Type of restaurant** (dine-in, delivery, quick bites, etc.).
- **Featured cuisines** and **meal types** available.

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Load the Dataset

```
df= pd.read_csv('Indian-Resturants.csv')
```

Display the first few rows of the dataset

```
df.head()
```

```
    res_id                            name      establishment  \
0  3400299                     Bikanervala    ['Quick Bites']
1  3400005  Mama Chicken Mama Franky House    ['Quick Bites']
2  3401013                   Bhagat Halwai    ['Quick Bites']
3  3400290                   Bhagat Halwai    ['Quick Bites']
4  3401744     The Salt Cafe Kitchen & Bar  ['Casual Dining']

                                                 url  \
0  https://www.zomato.com/agra/bikanervala-khanda...
1  https://www.zomato.com/agra/mama-chicken-mama-...
2  https://www.zomato.com/agra/bhagat-halwai-2-sh...
3  https://www.zomato.com/agra/bhagat-halwai-civi...
4  https://www.zomato.com/agra/the-salt-cafe-kitc...

                                             address  city  city_id  \
0  Kalyani Point, Near Tulsi Cinema, Bypass Road,...  Agra       34
1        Main Market, Sadar Bazaar, Agra Cantt, Agra  Agra       34
2  62/1, Near Easy Day, West Shivaji Nagar, Goalp...  Agra       34
3  Near Anjana Cinema, Nehru Nagar, Civil Lines, ...  Agra       34
4        1C,3rd Floor, Fatehabad Road, Tajganj, Agra  Agra       34

      locality   latitude  longitude  ... price_range  currency  \
0     Khandari  27.211450  78.002381  ...           2       Rs.
1   Agra Cantt  27.160569  78.011583  ...           2       Rs.
2     Shahganj  27.182938  77.979684  ...           1       Rs.
3  Civil Lines  27.205668  78.004799  ...           1       Rs.
4      Tajganj  27.157709  78.052421  ...           3       Rs.

                                          highlights aggregate_rating
\
0  ['Lunch', 'Takeaway Available', 'Credit Card',...              4.4

1  ['Delivery', 'No Alcohol Available', 'Dinner',...              4.4

2  ['No Alcohol Available', 'Dinner', 'Takeaway A...              4.2

3  ['Takeaway Available', 'Credit Card', 'Lunch',...              4.3

4  ['Lunch', 'Serves Alcohol', 'Cash', 'Credit Ca...              4.9
```

```
  rating_text  votes  photo_count opentable_support delivery  takeaway

0   Very Good    814          154                0.0       -1        -1

1   Very Good   1203          161                0.0       -1        -1

2   Very Good    801          107                0.0        1        -1

3   Very Good    693          157                0.0        1        -1

4   Excellent    470          291                0.0        1        -1


[5 rows x 26 columns]
```

information about the dataset

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 211944 entries, 0 to 211943
Data columns (total 26 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   res_id                211944 non-null  int64
 1   name                  211944 non-null  object
 2   establishment         211944 non-null  object
 3   url                   211944 non-null  object
 4   address               211810 non-null  object
 5   city                  211944 non-null  object
 6   city_id               211944 non-null  int64
 7   locality              211944 non-null  object
 8   latitude              211944 non-null  float64
 9   longitude             211944 non-null  float64
 10  zipcode               48757 non-null   object
 11  country_id            211944 non-null  int64
 12  locality_verbose      211944 non-null  object
 13  cuisines              210553 non-null  object
 14  timings               208070 non-null  object
 15  average_cost_for_two  211944 non-null  int64
 16  price_range           211944 non-null  int64
 17  currency              211944 non-null  object
 18  highlights            211944 non-null  object
 19  aggregate_rating      211944 non-null  float64
 20  rating_text           211944 non-null  object
 21  votes                 211944 non-null  int64
 22  photo_count           211944 non-null  int64
 23  opentable_support     211896 non-null  float64
 24  delivery              211944 non-null  int64
 25  takeaway              211944 non-null  int64
```

```
dtypes: float64(4), int64(9), object(13)
memory usage: 42.0+ MB
```

Shape and size of the dataset :

```
df.shape

(211944, 26)

df.size

5510544
```

Summarizing the Data

```
df.describe

<bound method NDFrame.describe of           res_id
name      establishment  \
0        3400299                        Bikanervala    ['Quick Bites']
1        3400005  Mama Chicken Mama Franky House    ['Quick Bites']
2        3401013                      Bhagat Halwai    ['Quick Bites']
3        3400290                      Bhagat Halwai    ['Quick Bites']
4        3401744     The Salt Cafe Kitchen & Bar  ['Casual Dining']
...          ...                             ...                ...
211939   3202251  Kali Mirch Cafe And Restaurant  ['Casual Dining']
211940   3200996                         Raju Omlet    ['Quick Bites']
211941  18984164                   The Grand Thakar  ['Casual Dining']
211942   3201138                             Subway    ['Quick Bites']
211943  18879846     Freshco's - The Health Cafe           ['Café']

                                                      url  \
0       https://www.zomato.com/agra/bikanervala-khanda...
1       https://www.zomato.com/agra/mama-chicken-mama-...
2       https://www.zomato.com/agra/bhagat-halwai-2-sh...
3       https://www.zomato.com/agra/bhagat-halwai-civi...
4       https://www.zomato.com/agra/the-salt-cafe-kitc...
...                                                   ...
211939  https://www.zomato.com/vadodara/kali-mirch-caf...
211940  https://www.zomato.com/vadodara/raju-omlet-kar...
211941  https://www.zomato.com/vadodara/the-grand-thak...
211942  https://www.zomato.com/vadodara/subway-1-akota...
211943  https://www.zomato.com/vadodara/freshcos-the-h...

                                                  address      city
city_id  \
0       Kalyani Point, Near Tulsi Cinema, Bypass Road,...      Agra
34
1             Main Market, Sadar Bazaar, Agra Cantt, Agra      Agra
34
```

```
2       62/1, Near Easy Day, West Shivaji Nagar, Goalp...      Agra
34
3       Near Anjana Cinema, Nehru Nagar, Civil Lines, ...      Agra
34
4             1C,3rd Floor, Fatehabad Road, Tajganj, Agra      Agra
34
...                                                   ...       ...
...
211939  Manu Smriti Complex, Near Navrachna School, GI...  Vadodara
32
211940  Mahalaxmi Apartment, Opposite B O B, Karoli Ba...  Vadodara
32
211941  3rd Floor, Shreem Shalini Mall, Opposite Conqu...  Vadodara
32
211942  G-2, Vedant Platina, Near Cosmos, Akota, Vadodara  Vadodara
32
211943  Shop 7, Ground Floor, Opposite Natubhai Circle...  Vadodara
32

           locality   latitude  longitude  ... price_range
currency  \
0          Khandari  27.211450  78.002381  ...           2       Rs.

1        Agra Cantt  27.160569  78.011583  ...           2       Rs.

2          Shahganj  27.182938  77.979684  ...           1       Rs.

3       Civil Lines  27.205668  78.004799  ...           1       Rs.

4           Tajganj  27.157709  78.052421  ...           3       Rs.

...             ...        ...        ...  ...         ...       ...

211939    Fatehgunj  22.336931  73.192356  ...           2       Rs.

211940   Karelibaug  22.322455  73.197203  ...           1       Rs.

211941     Alkapuri  22.310563  73.171163  ...           2       Rs.

211942        Akota  22.270027  73.143068  ...           2       Rs.

211943     Vadiwadi  22.309935  73.158768  ...           2       Rs.


                                               highlights
aggregate_rating  \
0       ['Lunch', 'Takeaway Available', 'Credit Card',...
4.4
1       ['Delivery', 'No Alcohol Available', 'Dinner',...
4.4
```

```
2         ['No Alcohol Available', 'Dinner', 'Takeaway A...
4.2
3         ['Takeaway Available', 'Credit Card', 'Lunch',...
4.3
4         ['Lunch', 'Serves Alcohol', 'Cash', 'Credit Ca...
4.9
...                                                     ...
...
211939    ['Dinner', 'Cash', 'Lunch', 'Delivery', 'Indoo...
4.1
211940    ['Dinner', 'Cash', 'Takeaway Available', 'Debi...
4.1
211941    ['Dinner', 'Cash', 'Debit Card', 'Lunch', 'Tak...
4.0
211942    ['Dinner', 'Delivery', 'Credit Card', 'Lunch',...
3.7
211943    ['Dinner', 'Cash', 'Takeaway Available', 'Debi...
4.0

       rating_text  votes  photo_count opentable_support delivery
takeaway
0        Very Good    814          154               0.0       -1
-1
1        Very Good   1203          161               0.0       -1
-1
2        Very Good    801          107               0.0        1
-1
3        Very Good    693          157               0.0        1
-1
4        Excellent    470          291               0.0        1
-1
...            ...    ...          ...               ...      ...
...
211939   Very Good    243           40               0.0       -1
-1
211940   Very Good    187           40               0.0        1
-1
211941   Very Good    111           38               0.0       -1
-1
211942        Good    128           34               0.0        1
-1
211943   Very Good     93           53               0.0        1
-1

[211944 rows x 26 columns]>
```

Checking for Unique values

```
df['city'].nunique()
```

```
99
```

```python
df['city'].unique()
```

```
array(['Agra', 'Ahmedabad', 'Gandhinagar', 'Ajmer', 'Alappuzha',
       'Allahabad', 'Amravati', 'Amritsar', 'Aurangabad', 'Bangalore',
       'Bhopal', 'Bhubaneshwar', 'Chandigarh', 'Mohali', 'Panchkula',
       'Zirakpur', 'Nayagaon', 'Chennai', 'Coimbatore', 'Cuttack',
       'Darjeeling', 'Dehradun', 'New Delhi', 'Gurgaon', 'Noida',
       'Faridabad', 'Ghaziabad', 'Greater Noida', 'Dharamshala',
       'Gangtok', 'Goa', 'Gorakhpur', 'Guntur', 'Guwahati', 'Gwalior',
       'Haridwar', 'Hyderabad', 'Secunderabad', 'Indore', 'Jabalpur',
       'Jaipur', 'Jalandhar', 'Jammu', 'Jamnagar', 'Jamshedpur',
'Jhansi',
       'Jodhpur', 'Junagadh', 'Kanpur', 'Kharagpur', 'Kochi',
'Kolhapur',
       'Kolkata', 'Howrah', 'Kota', 'Lucknow', 'Ludhiana', 'Madurai',
       'Manali', 'Mangalore', 'Manipal', 'Udupi', 'Meerut', 'Mumbai',
       'Thane', 'Navi Mumbai', 'Mussoorie', 'Mysore', 'Nagpur',
       'Nainital', 'Nasik', 'Nashik', 'Neemrana', 'Ooty', 'Palakkad',
       'Patiala', 'Patna', 'Puducherry', 'Pune', 'Pushkar', 'Raipur',
       'Rajkot', 'Ranchi', 'Rishikesh', 'Salem', 'Shimla', 'Siliguri',
       'Srinagar', 'Surat', 'Thrissur', 'Tirupati', 'Trichy',
       'Trivandrum', 'Udaipur', 'Varanasi', 'Vellore', 'Vijayawada',
       'Vizag', 'Vadodara'], dtype=object)
```

```python
df["price_range"].unique()
```

```
array([2, 1, 3, 4], dtype=int64)
```

```python
df["opentable_support"].unique()
```

```
array([ 0., nan])
```

```python
df["delivery"].unique()
```

```
array([-1,  1,  0], dtype=int64)
```

```python
df["takeaway"].unique()
```

```
array([-1], dtype=int64)
```

```python
df["currency"].unique()
```

```
array(['Rs.'], dtype=object)
```

```python
df[["aggregate_rating","votes","photo_count"]].describe().loc[["mean",
"min","max"]]
```

```
      aggregate_rating       votes  photo_count
mean          2.958593  223.330352    160.97477
```

```
min             0.000000    -18.000000      0.00000
max             4.900000  42539.000000  17702.00000
```

Data Cleaning

```
df['res_id'].duplicated() #to confirm the duplication
```

```
0         False
1         False
2         False
3         False
4         False
          ...
211939     True
211940    False
211941     True
211942    False
211943     True
Name: res_id, Length: 211944, dtype: bool
```

Removing Duplicates

```
df.drop_duplicates(["res_id"],keep="first",inplace=True)
df.shape
```

```
(55568, 26)
```

Removed or Not all duplicate values

```
df.duplicated().sum()
```

```
0
```

Missing Values are

```
df.isnull().sum()
```

```
res_id                       0
name                         0
establishment                0
url                          0
address                     18
city                         0
city_id                      0
locality                     0
latitude                     0
longitude                    0
zipcode                  44623
```

```
country_id                   0
locality_verbose             0
cuisines                   470
timings                   1003
average_cost_for_two         0
price_range                  0
currency                     0
highlights                   0
aggregate_rating             0
rating_text                  0
votes                        0
photo_count                  0
opentable_support           12
delivery                     0
takeaway                     0
dtype: int64
```

Cleaning 'establishment' Column

```
df["establishment"].unique()
```

```
array(["['Quick Bites']", "['Casual Dining']", "['Bakery']",
"['Café']",
       "['Dhaba']", "['Bhojanalya']", "['Bar']", "['Sweet Shop']",
       "['Fine Dining']", "['Food Truck']", "['Dessert Parlour']",
       "['Lounge']", "['Pub']", "['Beverage Shop']", "['Kiosk']",
       "['Paan Shop']", "['Confectionery']", '[]', "['Shack']",
       "['Club']", "['Food Court']", "['Mess']", "['Butcher Shop']",
       "['Microbrewery']", "['Cocktail Bar']", "['Pop up']",
       "['Irani Cafe']"], dtype=object)
```

```
print(df["establishment"].unique()[0])
print(type(df["establishment"].unique()[0]))
```

```
['Quick Bites']
<class 'str'>
```

```
# Removing [' '] from each value
print(df["establishment"].unique()[0])
df["establishment"] = df["establishment"].apply(lambda x:x[2:-2])
print(df["establishment"].unique()[0])

# Changing ''  to 'NA'
print(df["establishment"].unique())
df["establishment"] = df["establishment"].apply(lambda x :
np.where(x=="", "NA", x))
print(df["establishment"].unique())
```

```
['Quick Bites']
Quick Bites
```

```
['Quick Bites' 'Casual Dining' 'Bakery' 'Café' 'Dhaba' 'Bhojanalya'
'Bar'
 'Sweet Shop' 'Fine Dining' 'Food Truck' 'Dessert Parlour' 'Lounge'
'Pub'
 'Beverage Shop' 'Kiosk' 'Paan Shop' 'Confectionery' '' 'Shack' 'Club'
 'Food Court' 'Mess' 'Butcher Shop' 'Microbrewery' 'Cocktail Bar' 'Pop
up'
 'Irani Cafe']
['Quick Bites' 'Casual Dining' 'Bakery' 'Café' 'Dhaba' 'Bhojanalya'
'Bar'
 'Sweet Shop' 'Fine Dining' 'Food Truck' 'Dessert Parlour' 'Lounge'
'Pub'
 'Beverage Shop' 'Kiosk' 'Paan Shop' 'Confectionery' 'NA' 'Shack'
'Club'
 'Food Court' 'Mess' 'Butcher Shop' 'Microbrewery' 'Cocktail Bar' 'Pop
up'
 'Irani Cafe']

df1 = df.drop(columns=['url', 'address', 'zipcode','timings'])

df1["cuisines"].unique()

array(['North Indian, South Indian, Mithai, Street Food, Desserts',
       'North Indian, Mughlai, Rolls, Chinese, Fast Food, Street
Food',
       'Fast Food, Mithai', ...,
       'Street Food, Biryani, Chinese, Fast Food, North Indian,
Mughlai',
       'North Indian, Chinese, Mexican, Italian, Thai, Continental',
       'North Indian, Lucknowi, Chinese'], dtype=object)

df1 = df1.dropna(subset=['cuisines'])
```

Filling Null Values

```
mode_value = df1['opentable_support'].mode()[0]
df1['opentable_support'] = df1['opentable_support'].fillna(mode_value)

print(f"Average Rating: {df1['aggregate_rating'].mean()}")

Average Rating: 2.97947838397038

df1.describe() #this is the way to get statistical analysis of all the
values

             res_id       city_id      latitude     longitude
country_id  \
count  5.509800e+04  55098.000000  55098.000000  55098.000000
55098.0
mean   1.309156e+07   3354.276997     21.432702     76.511880
1.0
```

```
std     8.122561e+06   5150.396004     43.079375     10.937547
0.0
min     5.000000e+01      1.000000      0.000000      0.000000
1.0
25%     3.000944e+06      8.000000     16.511407     74.747339
1.0
50%     1.869208e+07     26.000000     22.465234     77.104666
1.0
75%     1.887349e+07  11294.000000     26.752206     79.831778
1.0
max     1.915979e+07  11354.000000  10000.000000     91.832769
1.0

       average_cost_for_two   price_range  aggregate_rating
votes  \
count           55098.000000  55098.000000      55098.000000
55098.000000
mean              531.792697      1.719591          2.979478
225.210008
std               595.916590      0.879407          1.449025
620.517701
min                 0.000000      1.000000          0.000000    -
18.000000
25%               200.000000      1.000000          2.900000
6.000000
50%               350.000000      1.000000          3.500000
36.000000
75%               600.000000      2.000000          3.900000
177.000000
max             30000.000000      4.000000          4.900000
42539.000000

        photo_count  opentable_support      delivery  takeaway
count  55098.000000            55098.0  55098.000000   55098.0
mean     162.336782                0.0     -0.345003      -1.0
std      589.287353                0.0      0.935579       0.0
min        0.000000                0.0     -1.000000      -1.0
25%        1.000000                0.0     -1.000000      -1.0
50%       10.000000                0.0     -1.000000      -1.0
75%       70.000000                0.0      1.000000      -1.0
max    17702.000000                0.0      1.000000      -1.0
```

```
df1[['price_range', 'aggregate_rating']].describe()
```

```
        price_range  aggregate_rating
count  55098.000000      55098.000000
mean       1.719591          2.979478
std        0.879407          1.449025
min        1.000000          0.000000
25%        1.000000          2.900000
```

```
50%        1.000000          3.500000
75%        2.000000          3.900000
max        4.000000          4.900000
```

```
df1.describe(include=['object']) #getting description for all the categorical or descriptive columns
```

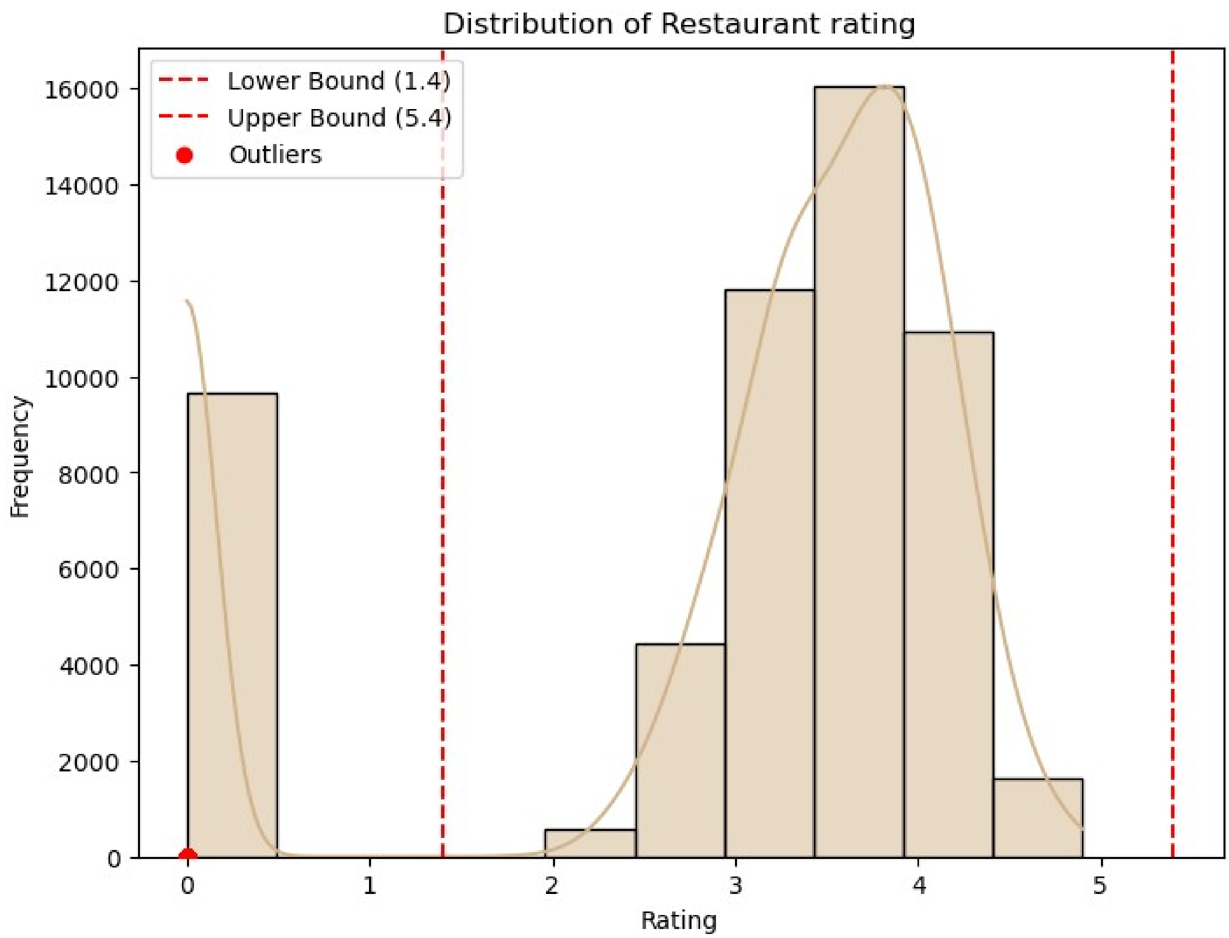
```
                  name establishment       city      locality  \
count            55098         55098      55098         55098
unique           40757            27         99          3727
top      Domino's Pizza   Quick Bites  Bangalore   Civil Lines
freq               399         14000       2247           751

            locality_verbose      cuisines currency  \
count                  55098         55098    55098
unique                  3905          9382        1
top      Gomti Nagar, Lucknow  North Indian      Rs.
freq                     274          4295    55098

                                               highlights rating_text

count                                               55098       55098

unique                                              31167          33

top     ['Dinner', 'Takeaway Available', 'Lunch', 'Cas...     Average

freq                                                  860       16256
```

Outliers if any:

```
# calculate the IQR
Q1=df1['aggregate_rating'].quantile(0.25)
Q3=df1['aggregate_rating'].quantile(0.75)
IQR=Q3-Q1

lower_bound = Q1 - 1.5*IQR
upper_bound = Q3 + 1.5*IQR

# Identify outliers
outliers = df1[(df1['aggregate_rating'] < lower_bound) |
(df1['aggregate_rating'] > upper_bound)]

print(f"Q1: {Q1}")
print(f"Q3: {Q3}")
print(f"IQR: {IQR}")
print(f"lower: {lower_bound}")
print(f"upper: {upper_bound}")
```

```
Q1: 2.9
Q3: 3.9
IQR: 1.0
lower: 1.4
upper: 5.4
```

```
# Create a histogram to visualize the distribution of the data
plt.figure(figsize=(8, 6))
sns.histplot(df1['aggregate_rating'], bins=10, kde=True,
color='#D2B48C', edgecolor='black')

plt.axvline(x=lower_bound, color='red', linestyle='--', label=f'Lower
Bound ({lower_bound})')
plt.axvline(x=upper_bound, color='red', linestyle='--', label=f'Upper
Bound ({upper_bound})')


outlier_values = df1[(df1['aggregate_rating'] < lower_bound) |
(df1['aggregate_rating'] > upper_bound)]['aggregate_rating']
plt.scatter(outlier_values, np.zeros_like(outlier_values),
color='red', label='Outliers', zorder=5)

plt.title('Distribution of Restaurant rating')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.legend()

plt.show()
```

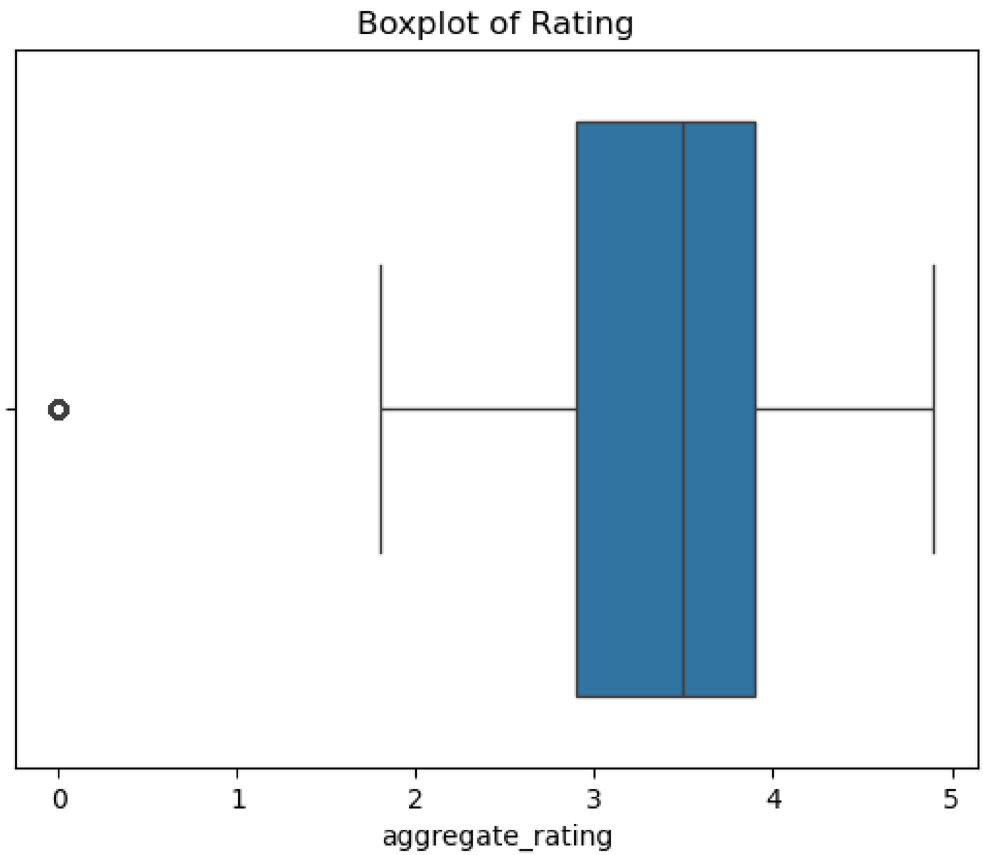


Observations: The restaurant ratings follow a right-skewed distribution, with most ratings falling between 3 and 4. There are also outliers below the lower bound, indicating some exceptionally low ratings. Recommendations: Promote High-Rated Restaurants Focus on marketing and promotional efforts for restaurants with ratings of 4 or higher to attract more customers. Improve Low-Rated Restaurants Investigate the causes of low ratings and implement corrective measures, such as enhancing: Service quality Food quality Ambience Analyze Customer Feedback Continuously monitor and analyze customer feedback to pinpoint areas that need improvement. Make necessary adjustments based on customer suggestions and reviews.

Boxplot

```
sns.boxplot(x='aggregate_rating', data=df1)
plt.title('Boxplot of Rating')
plt.show()

# Calculate quartiles
Q1 = df1['aggregate_rating'].quantile(0.25)
Q3 = df1['aggregate_rating'].quantile(0.75)
IQR = Q3 - Q1
```

```
threshold = 1.5 * IQR

outliers = df1[(df1['aggregate_rating'] < Q1 - threshold) |
(df1['aggregate_rating'] > Q3 + threshold)]
```



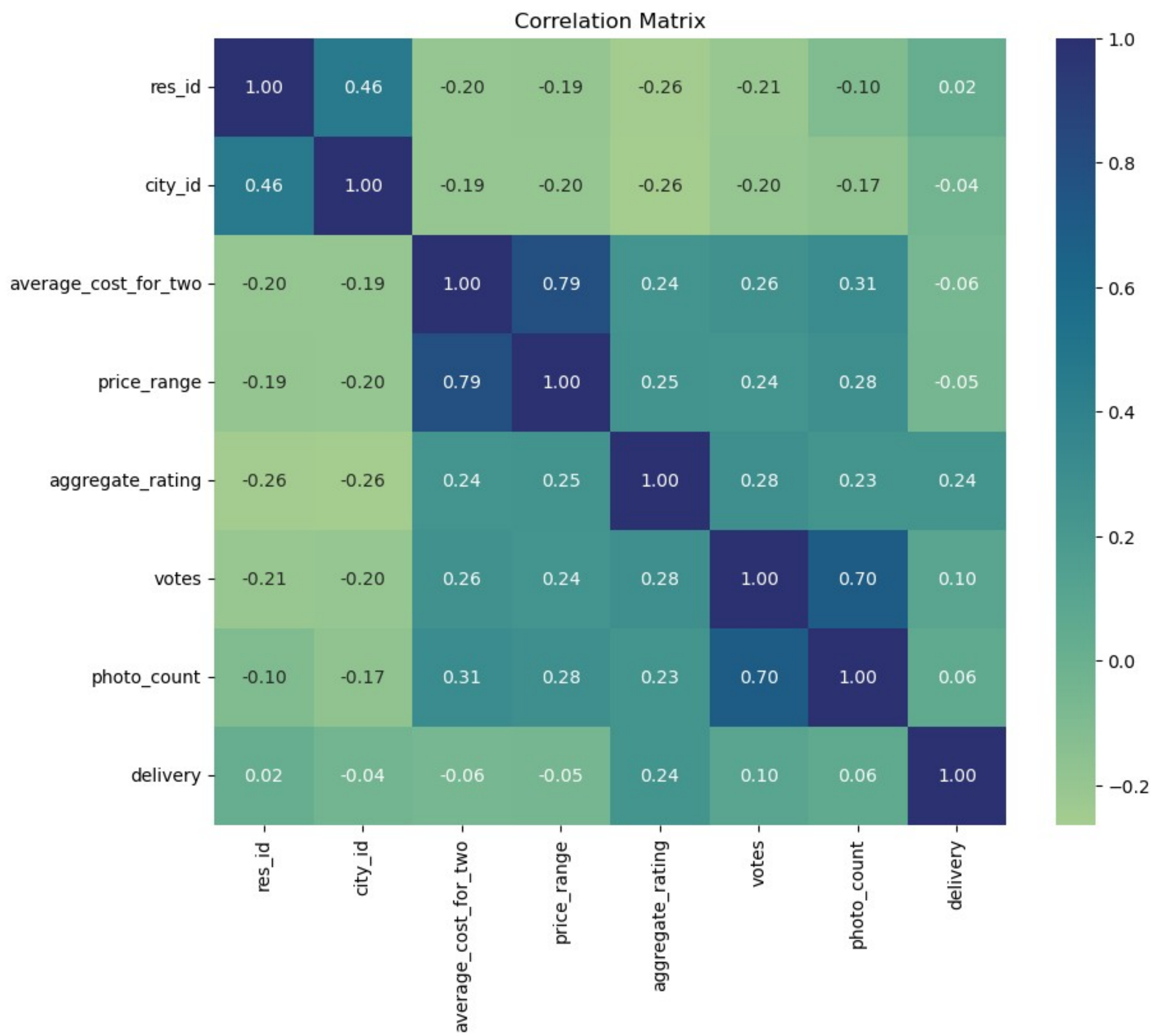
Observations from the Boxplot of Aggregate Ratings 1 Right-Skewed Distribution The median is positioned closer to the upper quartile (Q3), indicating a right-skewed distribution. The majority of ratings are concentrated between 3 and 4.5, with fewer ratings on the lower end. 2 Presence of an Outlier A single outlier is observed at 0 (on the far left). This suggests that at least one restaurant has an exceptionally low rating, which may warrant further investigation. 3 Interquartile Range (IQR) The middle 50% of ratings (from Q1 to Q3) fall between 2.5 and 4.5. The whiskers extend from roughly 1.5 to 5, representing the overall range of most ratings.

outliers

```
df1['aggregate_rating'] = df1['aggregate_rating'].clip(lower=Q1 -
threshold, upper=Q3 + threshold)

sns.boxplot(x='aggregate_rating', data=df1,color='#F4A460')
plt.title('Boxplot of aggregate_rating after Outlier Treatment')
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[15], line 1
----> 1 sns.boxplot(x='aggregate_rating', data=df1,color='#F4A460')
      2 plt.title('Boxplot of aggregate_rating after Outlier Treatment')
      3 plt.show()

NameError: name 'sns' is not defined
```

```
correlation = df2.select_dtypes(include=['number']).corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation, annot=True, cmap="crest", fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
res_id
city_id
average_cost_for_two
price_range
aggregate_rating
votes
photo_count
delivery
1.00 0.46 -0.20 -0.19 -0.26 -0.21 -0.10 0.02
0.46 1.00 -0.19 -0.20 -0.26 -0.20 -0.17 -0.04
-0.20 -0.19 1.00 0.79 0.24 0.26 0.31 -0.06
-0.19 -0.20 0.79 1.00 0.25 0.24 0.28 -0.05
-0.26 -0.26 0.24 0.25 1.00 0.28 0.23 0.24
-0.21 -0.20 0.26 0.24 0.28 1.00 0.70 0.10
-0.10 -0.17 0.31 0.28 0.23 0.70 1.00 0.06
0.02 -0.04 -0.06 -0.05 0.24 0.10 0.06 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

It is evident that for there is positive correlation between photo count and votes. It can be infered that all popular restuarants have their photos available. Moreover, price range is also related to costs for two. The higher the costs for two is resturants will fall in the place of high range for price

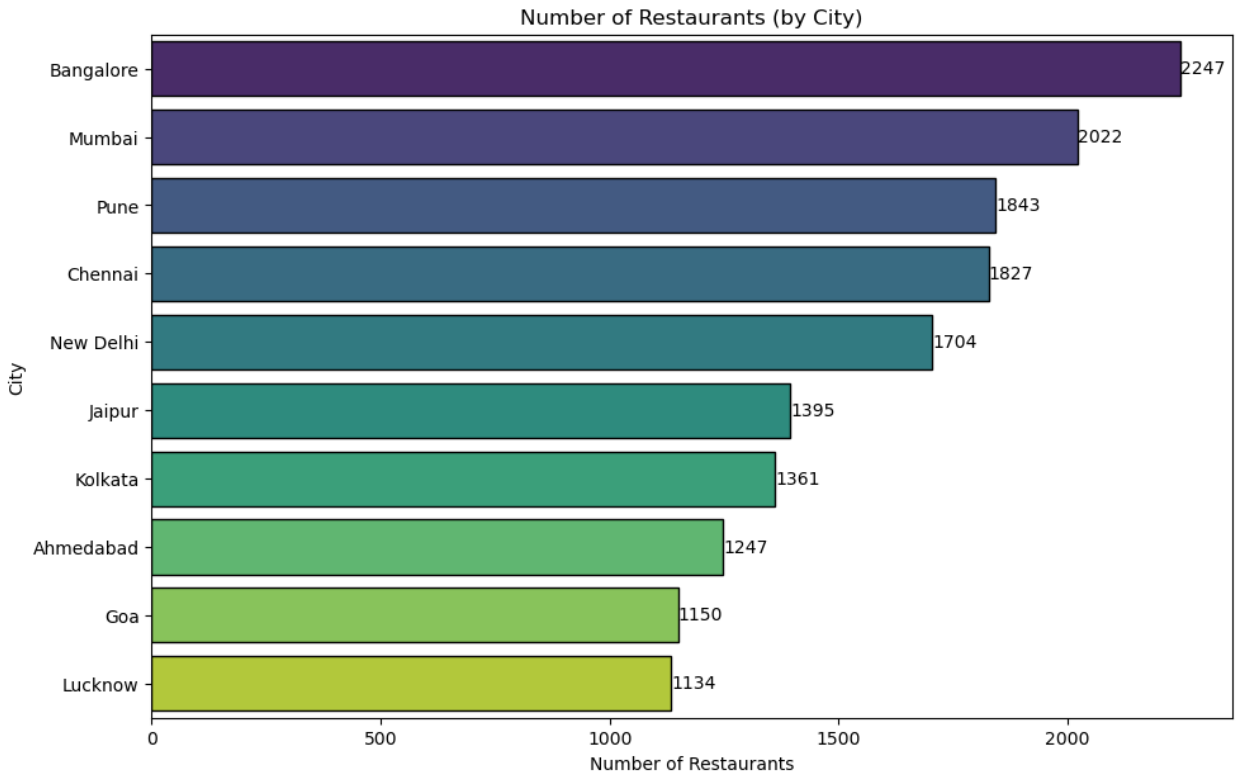
Data Visualization

1.Location Analysis

1.1 Cities with the highest concentration of restaurants

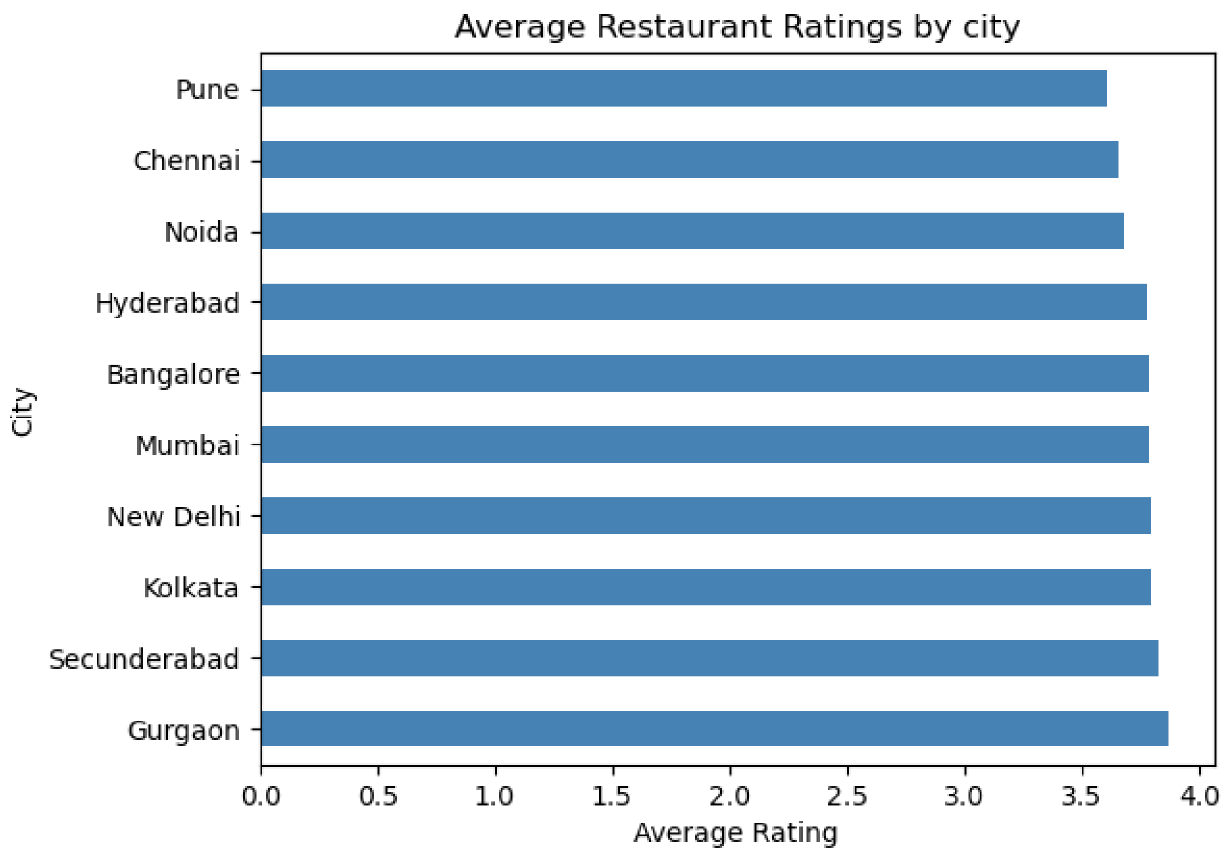
```
df1['city'].value_counts()

city
Bangalore        2247
Mumbai           2022
Pune             1843
Chennai          1827
New Delhi        1704
                 ...
Udupi              60
Howrah             50
Neemrana           26
Greater Noida      21
Nayagaon           15
Name: count, Length: 99, dtype: int64


# Calculate the value counts for the top 10 cities
city_counts = df1.groupby("city").count()
["res_id"].sort_values(ascending=False).head(10)
city_counts_df = city_counts.reset_index()
city_counts_df.columns = ["City", "Number of Restaurants"]

colors = sns.color_palette("viridis", len(city_counts_df))

plt.figure(figsize=(11, 7))
sns.barplot(
    x="Number of Restaurants",
    y="City",
    data=city_counts_df,
    palette=colors,  # Apply viridis colors
    edgecolor="black"
)
```

```
for index, value in enumerate(city_counts_df["Number of
Restaurants"]):
    plt.text(value, index, str(value), color="black", ha="left",
va="center")

plt.xlabel("Number of Restaurants")
plt.ylabel("City")
plt.title("Number of Restaurants (by City)")

plt.show()
```



Rating by city

```
city_counts = df1['city'].value_counts()
city_ratings = df1.groupby('city')['aggregate_rating'].mean()
city_ratings.sort_values(ascending=False).head(10).plot(kind='barh',
color='#4682B4')
plt.title('Average Restaurant Ratings by city')
plt.xlabel('Average Rating')
plt.ylabel('City')
plt.show()
```



Observations:

- The average restaurant ratings are relatively high across all cities, with Gurgaon having the highest average rating.
- There is not a significant difference in ratings between cities.

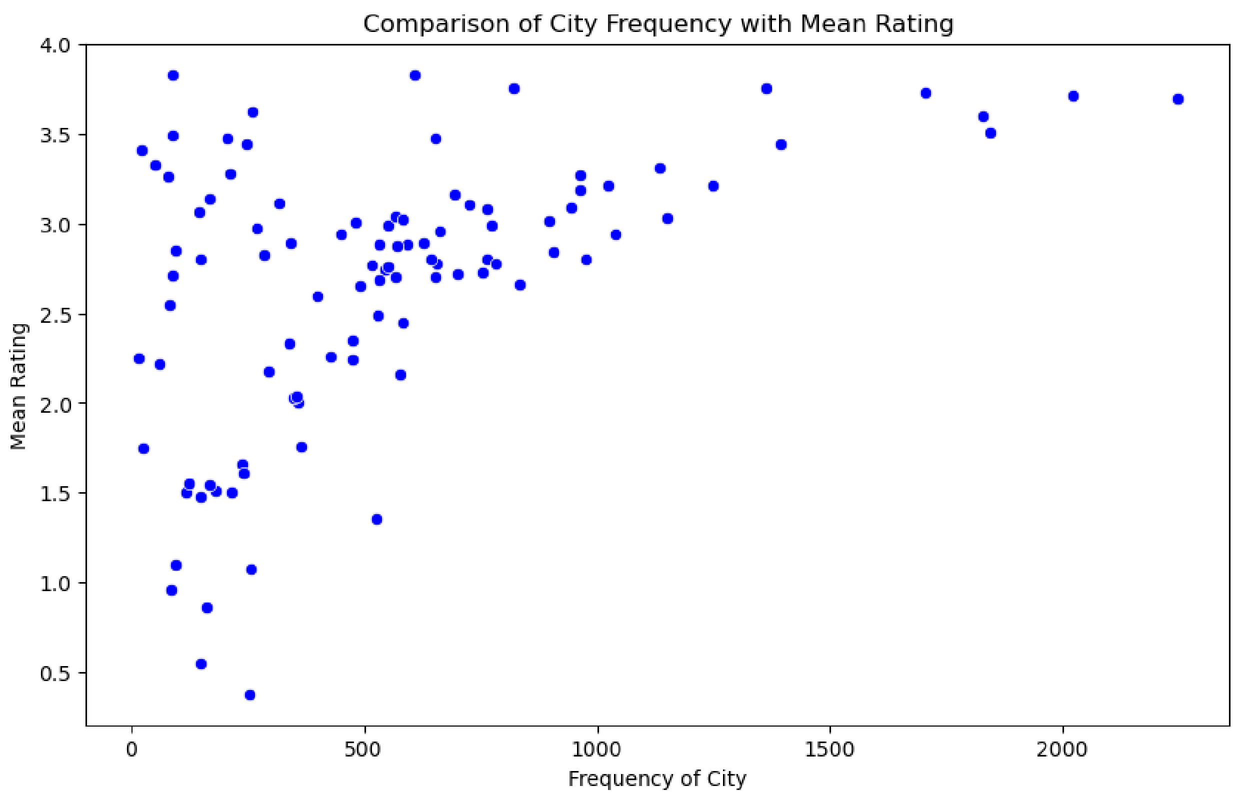
Recommendations:

- **Maintain High Standards**: Zomato should continue to maintain high standards for restaurant partners to ensure consistent quality across all cities.
- **Targeted Marketing**: While all cities have high ratings, targeted marketing campaigns can be implemented to highlight specific cuisines, restaurants, or promotions in each city to drive sales.
- **Customer Feedback Analysis**: Regularly analyze customer feedback and reviews to identify areas for improvement and implement necessary changes in specific cities.

Comparison

```
city_stats = df1.groupby('city').agg(mean_rating=('aggregate_rating',
'mean'), frequency=('city', 'size')).reset_index()

# Set up the figure and axes
plt.figure(figsize=(10, 6))
```

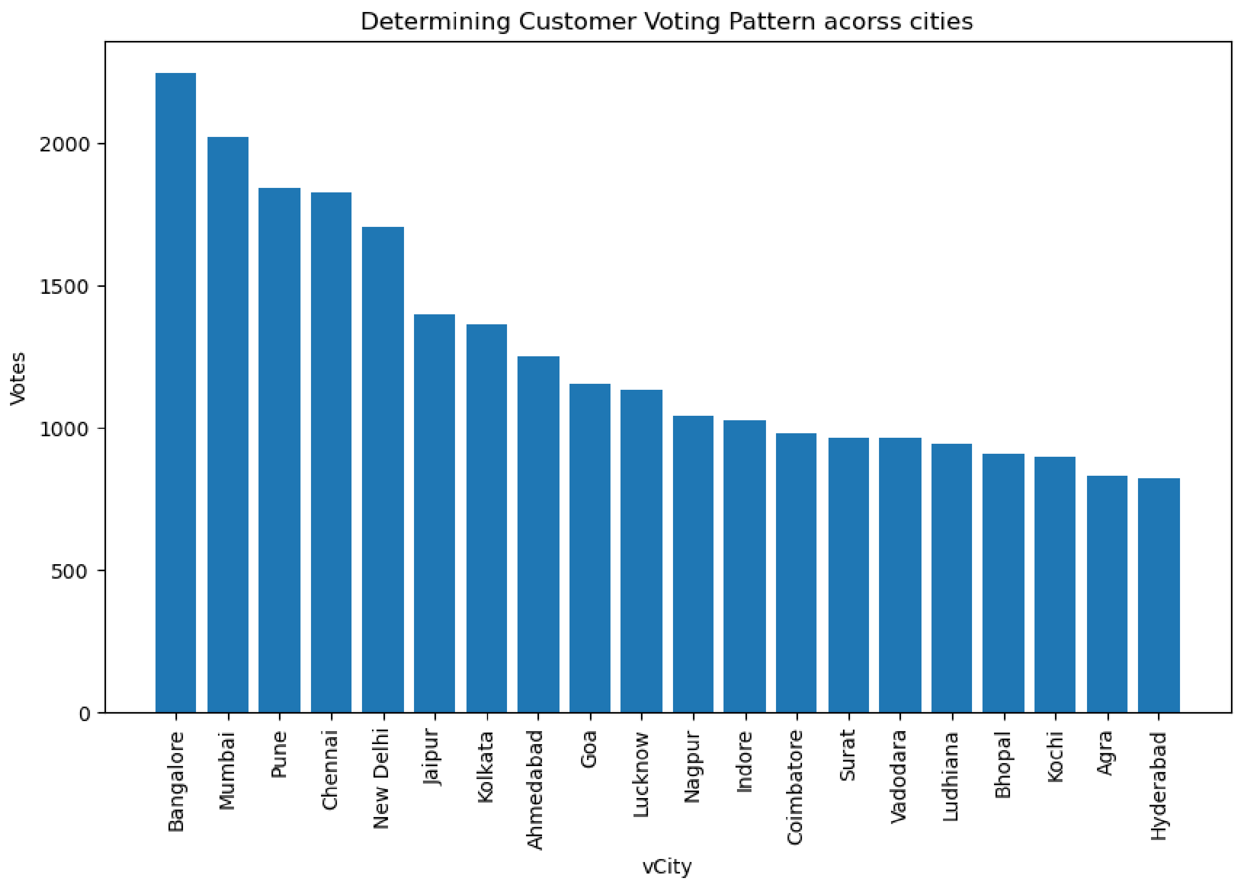
```
# Create scatter plot
sns.scatterplot(x='frequency', y='mean_rating', data=city_stats,
color='blue')

# Add labels and title
plt.xlabel('Frequency of City')
plt.ylabel('Mean Rating')
plt.title('Comparison of City Frequency with Mean Rating')

# Show the plot
plt.show()
```



Total Votes Distribution BY Cities

```
estb = df1.groupby('city')['votes'].size().reset_index()
estb1 = estb.sort_values(by='votes', ascending=False)
top10estb = estb1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top10estb['city'], top10estb['votes'])
# Add labels and title
```

```
plt.xlabel('vCity')
plt.ylabel('Votes')
plt.title('Determining Customer Voting Pattern acorss cities')
plt.xticks(rotation=90)

plt.show()
```



Bangalore has overall most number of votes . It is followed by Mumbai and others as depicted in above visual

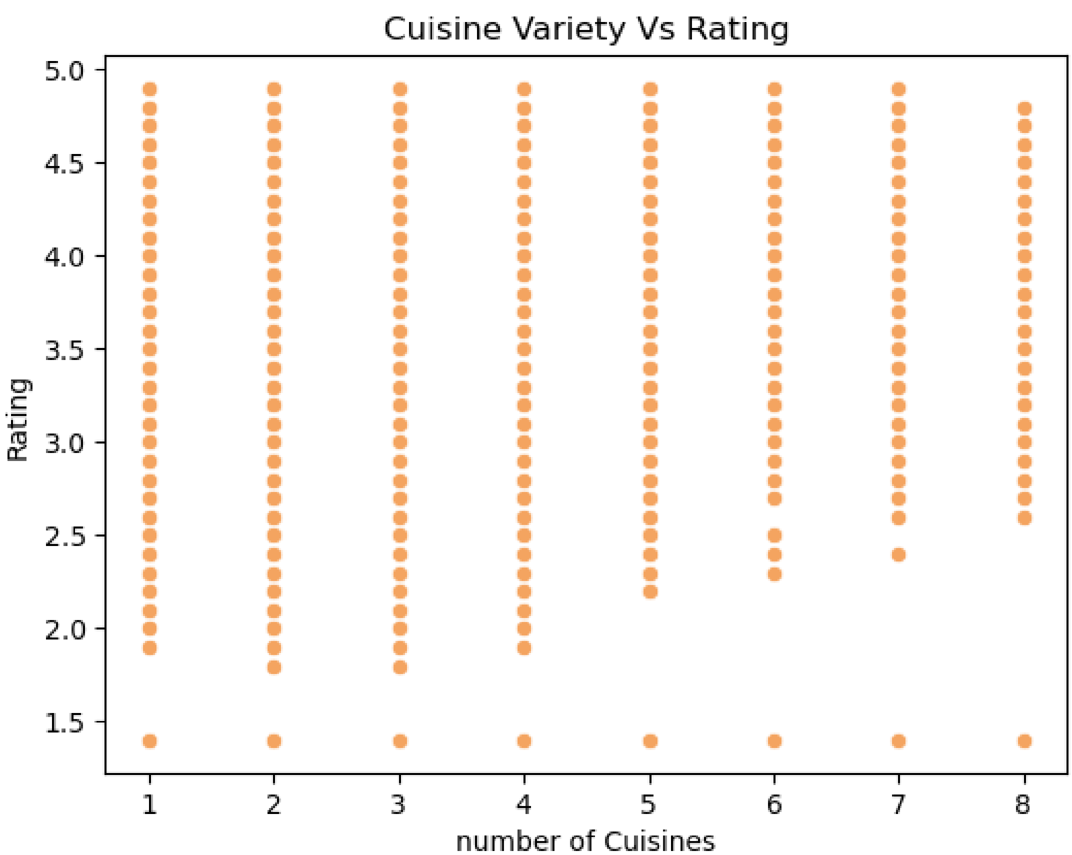
Cuisine Analysis:

Checking most popular cuisines among the listed restaurants :

```
cuisine_counts = df['cuisines'].value_counts()
cuisine_counts.head(10)
```

```
cuisines
North Indian                4295
Fast Food                   2025
North Indian, Chinese       1636
Bakery                      1585
South Indian                1489
Street Food                 1187
Cafe                        1098
Mithai                      1020
Desserts                     922
Bakery, Desserts             836
Name: count, dtype: int64
```

```
df1['new_cuisines'] = df1['cuisines'].apply(lambda x:
len(x.split(',')))
sns.scatterplot(x='new_cuisines',y='aggregate_rating',data=df1,color='
#F4A460')
plt.title('Cuisine Variety Vs Rating')
plt.xlabel('number of Cuisines')
plt.ylabel('Rating')
plt.show()
```



Observations:

- There doesn't seem to be a strong correlation between the number of cuisines offered by a restaurant and its rating.
- Restaurants with a wide range of cuisines (up to 8) have similar ratings to those with fewer cuisines.

Recommendations:

- **Focus on Quality Over Quantity**: Rather than focusing on offering a wide variety of cuisines, restaurants should prioritize offering high-quality dishes within a few core cuisines.
- **Customer Feedback Analysis**: Analyze customer feedback to understand the most popular cuisines and dishes, and focus on improving these offerings.
- **Unique Selling Proposition**: Restaurants should aim to differentiate themselves by offering unique dishes or dining experiences, rather than simply focusing on the number of cuisines.
- **Efficient Operations**: Offering a wide variety of cuisines can increase operational complexity and costs. Restaurants should focus on streamlining operations and optimizing their menu to maintain quality and profitability.

Restaurants by Cuisine :

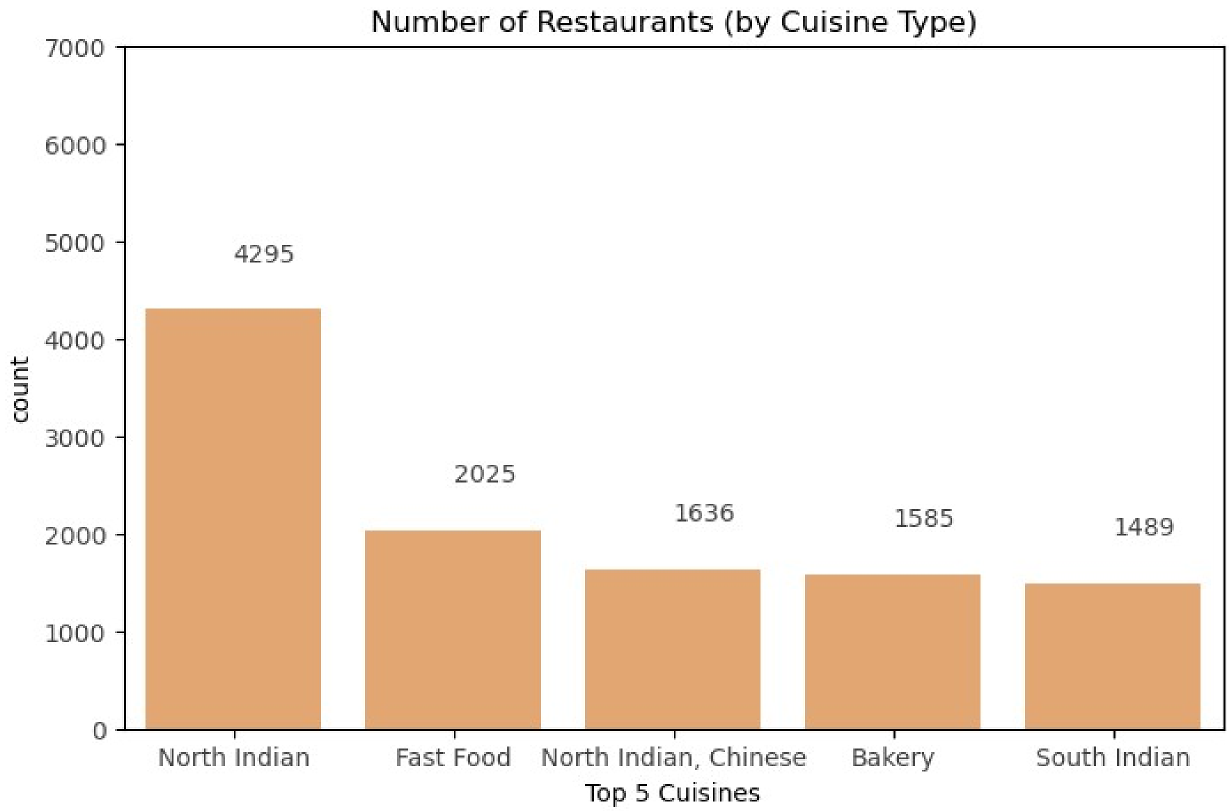
```
cuisiness = df1['cuisines']
# Calculate the top 5 cuisines
cuisines_count = cuisiness.value_counts()[:5].reset_index()
cuisines_count.columns = ['cuisine', 'count']
cuisines_count
```

	cuisine	count
0	North Indian	4295
1	Fast Food	2025
2	North Indian, Chinese	1636
3	Bakery	1585
4	South Indian	1489

Top 5 cuisines

```
# Plotting with Seaborn
plt.figure(figsize=(8, 5))
sns.barplot(x='cuisine', y='count',
data=cuisines_count,color='#F4A460')
plt.xticks(color="#424242")
plt.yticks(range(0, 8000, 1000), color="#424242")
plt.xlabel("Top 5 Cuisines")
plt.title("Number of Restaurants (by Cuisine Type)")

for index, value in enumerate(cuisines_count['count']):
```

```python
    plt.text(index, value + 500, str(value), color='#424242')
plt.show()
```



North Indian Cuisine Dominates

- With **4,295 restaurants** offering North Indian cuisine, it significantly surpasses other cuisine types, indicating its **high popularity and demand** across cities.

Fast Food on the Rise

- **Fast Food** takes the second spot with **2,025 outlets**, showcasing the growing influence of **quick and convenient dining options**, especially among younger demographics.

Fusion Appeal of North Indian and Chinese

- The combination of **North Indian and Chinese cuisines**, offered by **1,636 restaurants**, highlights the growing demand for **diverse and fusion dining experiences**.

Bakery and South Indian are Close Competitors

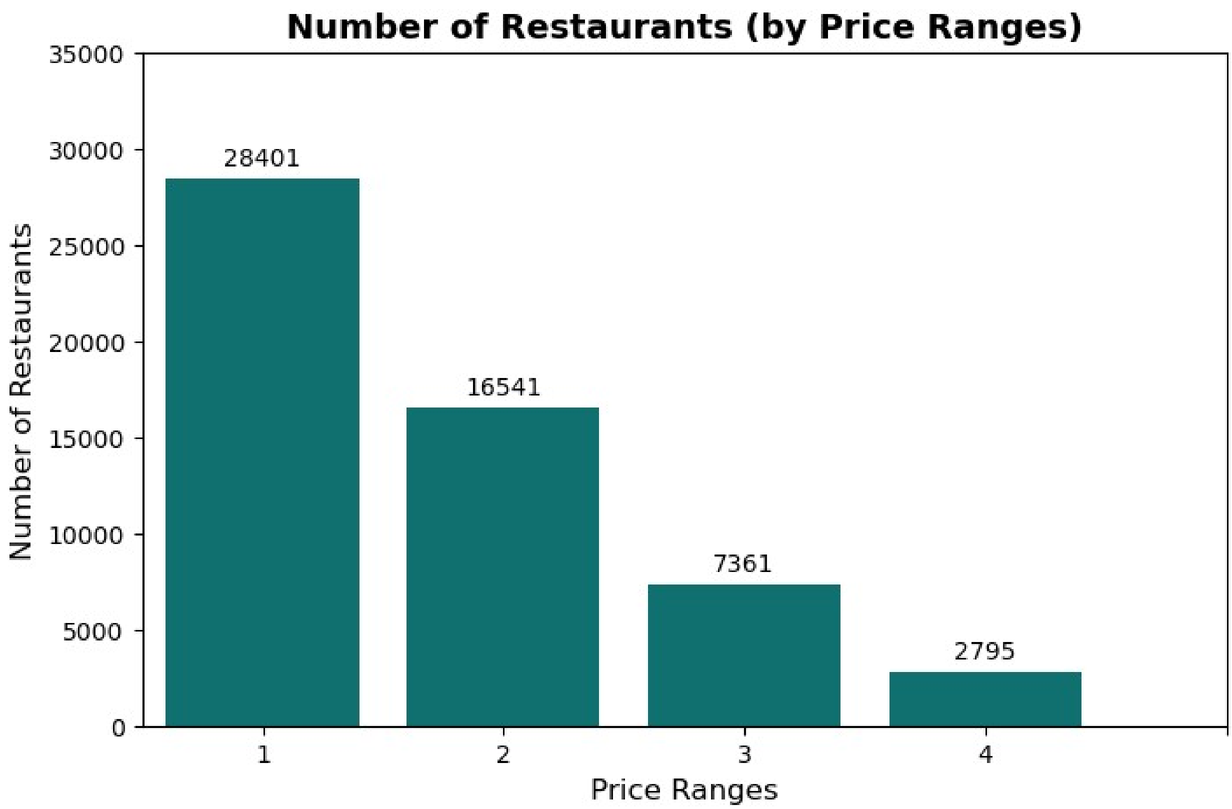
- **Bakery (1,585)** and **South Indian (1,489)** cuisines have a strong presence, indicating their **consistent appeal as comfort food and traditional staples**, respectively.

Insights on Trends

- **Cultural Significance:** The dominance of North Indian cuisine reflects its **widespread acceptance and cultural roots** in the Indian dining space.
- **Fusion Opportunities**: The demand for mixed cuisines like **North Indian and Chinese** points toward opportunities for **innovative food combinations**.
- **Changing Preferences:** The growth in **Fast Food restaurants** indicates **shifting consumer preferences** toward **convenience-driven dining**.

Price Range Count

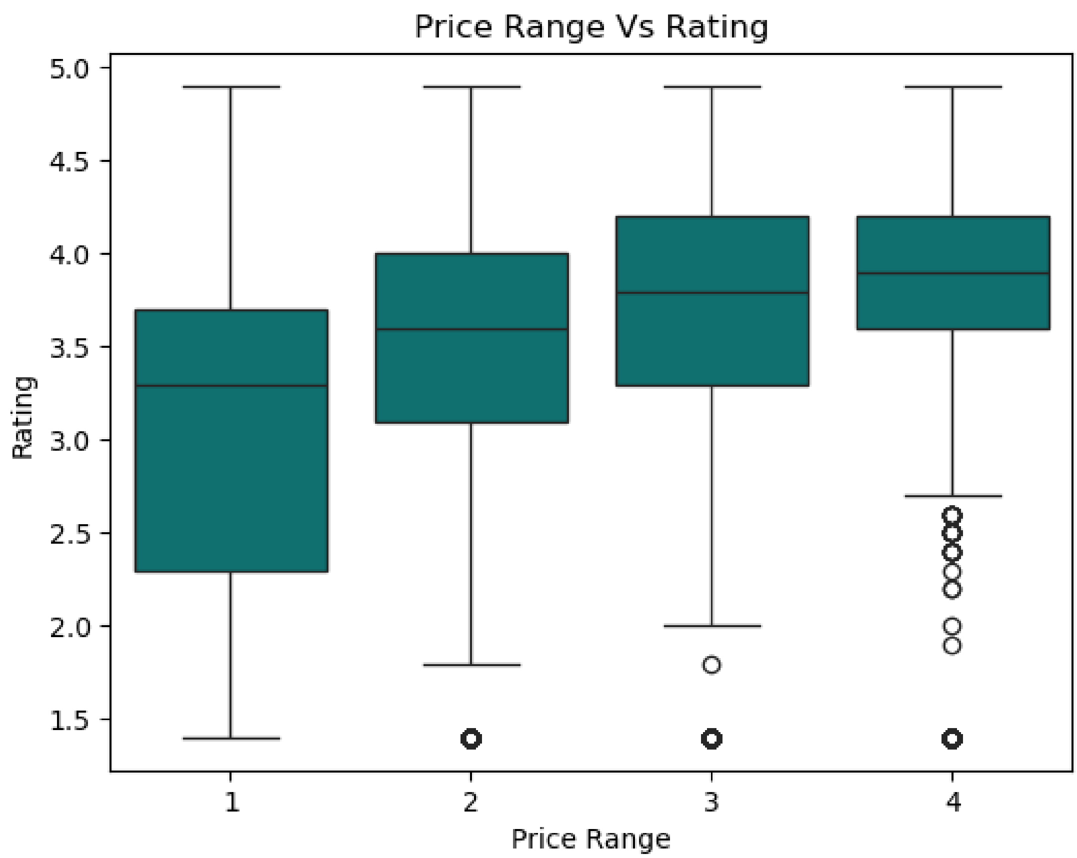
```
# Calculate the value counts for price ranges
pr_count = df1.groupby("price_range").count()["name"].reset_index()
pr_count.columns = ['price_range', 'count']


plt.figure(figsize=(8, 5))
sns.barplot(x='price_range', y='count', data=pr_count, color="#008080")

plt.xticks(range(0, 5), color="black")  # Changed from white to black for visibility
plt.yticks(range(0, 40000, 5000), color="black")  # Changed from white to black
plt.xlabel("Price Ranges", color="black", fontsize=12)  # Updated font size for clarity
plt.ylabel("Number of Restaurants", color="black", fontsize=12)
plt.title("Number of Restaurants (by Price Ranges)", color="black", fontsize=14, fontweight='bold')

for index, value in enumerate(pr_count['count']):
    plt.text(index, value + 700, str(value), color='black', ha='center', fontsize=10)

plt.show()
```



Price range chart supports our previous observation from the Average cost chart. Number of restaurant decreases with increase in price range

Relationship Calculating

```
sns.boxplot(data=df1,x='price_range',y='aggregate_rating',color="#0080
80")
plt.title('Price Range Vs Rating')
plt.xlabel('Price Range')
plt.ylabel('Rating')
plt.show()
```



Now, it is clear. The higher the price a restaurant charges, more services they provide and hence more chances of getting good ratings from their customers.

Calculating the average cost for two people in different price categories

```
price_rating = df1.groupby('price_range')
['average_cost_for_two'].mean()
price_rating

price_range
1     219.258125
2     522.320839
3    1091.659965
4    2289.139893
Name: average_cost_for_two, dtype: float64
```

Categorizing Restaurants by Online Order Availability:

```
delivery_group = df1.groupby('delivery')['aggregate_rating'].median()
delivery_group
```

```
delivery
-1    3.3
 0    3.3
 1    3.7
Name: aggregate_rating, dtype: float64
```

Visualize the Impact on Ratings :

```
sns.boxplot(x='delivery', y='aggregate_rating',
data=df1,color='#AED6F1')
plt.title('Impact of Online Orders on Restaurant Ratings')
plt.xlabel('Delivery Available (1 = Yes, 0 = No)')
plt.ylabel('Aggregate Rating')
plt.show()
```

Number of Restaurants Offering Table Booking :

```
df1['opentable_support'].value_counts()
```

```
opentable_support
0.0    55098
Name: count, dtype: int64
```

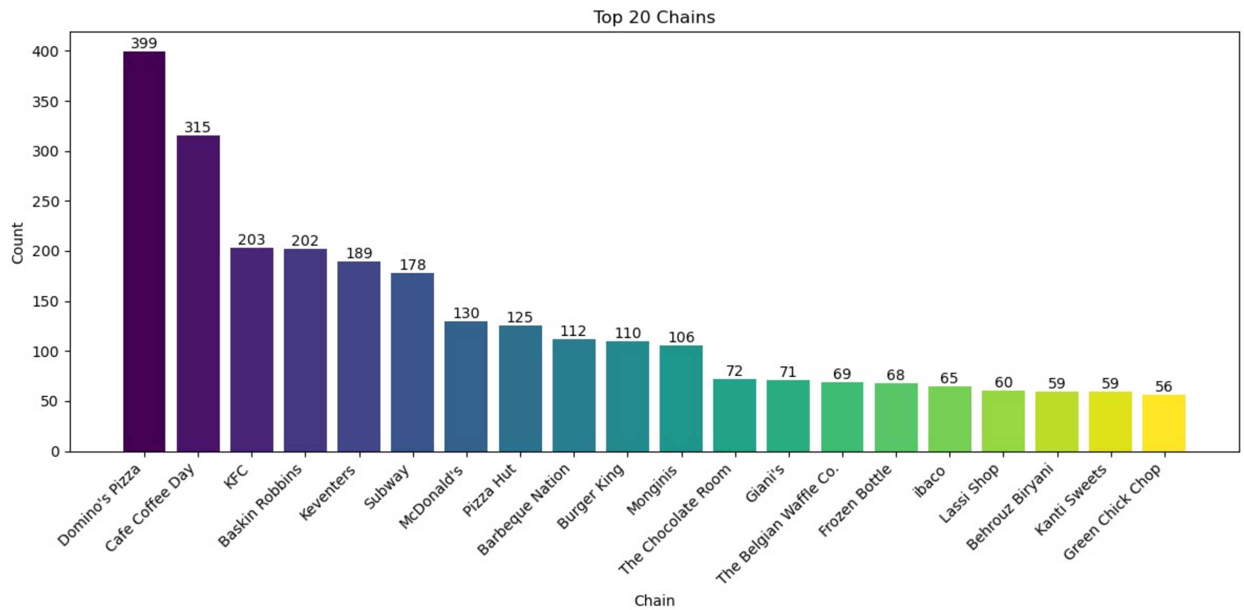
Top Restaurant Chains

```
restaurant_counts = df1['name'].value_counts()
top_chains = restaurant_counts.head(10)
top_chains
```

```
name
Domino's Pizza      399
Cafe Coffee Day     315
KFC                 203
Baskin Robbins      202
Keventers           189
Subway              178
McDonald's          130
Pizza Hut           125
Barbeque Nation     112
Burger King         110
Name: count, dtype: int64
```

Top 20 chains Based on Outlets

```
chain_counts1 = df1['name'].value_counts().head(20)

plt.figure(figsize=(12, 6))

colors = plt.cm.viridis(np.linspace(0, 1, len(chain_counts1)))

bars = plt.bar(chain_counts1.index, chain_counts1.values,
color=colors)

plt.xlabel('Chain')
plt.ylabel('Count')
plt.title('Top 20 Chains')

plt.xticks(rotation=45, ha='right')
plt.tight_layout()

for bar in bars:
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height(),
             str(bar.get_height()), ha='center', va='bottom',
fontsize=10)

plt.show()
```



Observations & Recommendations

Observations

- **Leading Restaurant Chain: Domino's Pizza** has the highest number of outlets, followed by **Cafe Coffee Day**.

- **Other Major Chains: KFC, Subway, and Keventers** also have a significant presence in the market.

Recommendations

1. **Strategic Partnerships:** Zomato can collaborate with these top restaurant chains to provide **exclusive deals, discounts, and loyalty programs** to attract more customers.

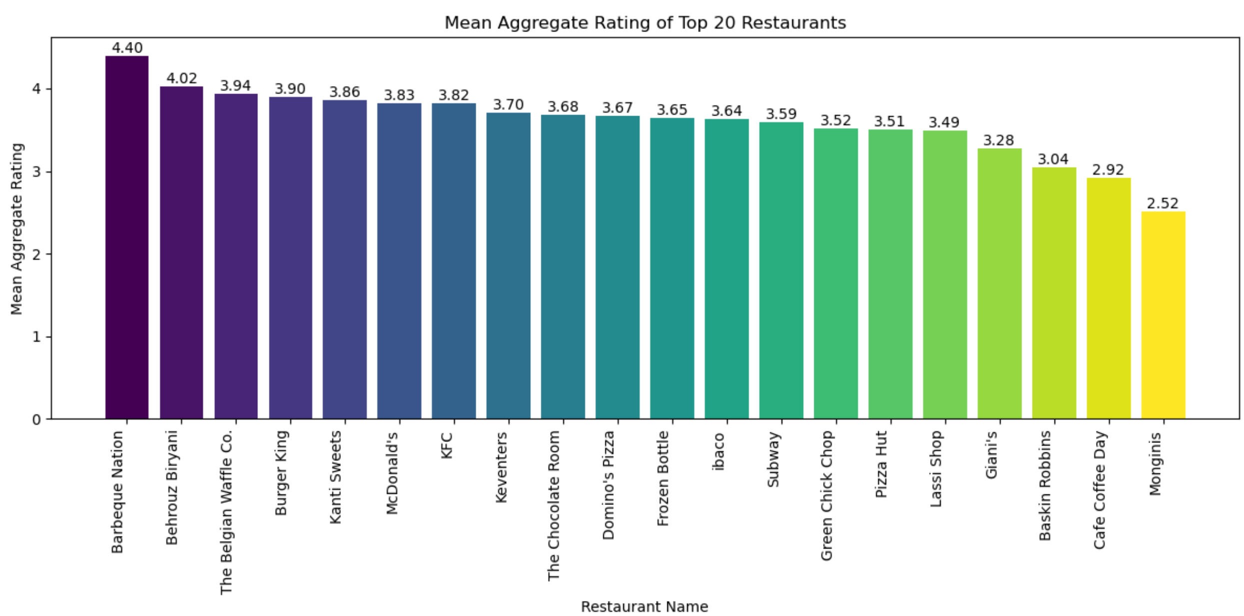
2. **Data-Driven Insights:** Leveraging **data analytics** can help identify high-performing outlets and optimize **marketing strategies** for better engagement.

3. **Geographic Expansion:** Encourage these chains to **expand in high-demand areas** with limited competition to maximize market penetration.

Top 20 resturants Based on Ratings

```
chain_counts1 = df1['name'].value_counts().head(20)

chain_counts = df1.groupby('name')
['aggregate_rating'].mean().reset_index()

chain_counts =
chain_counts[chain_counts['name'].isin(chain_counts1.index)]
```

```
chain_counts = chain_counts.sort_values(by=['aggregate_rating'],
ascending=False)

colors = plt.cm.viridis(np.linspace(0, 1, len(chain_counts)))

plt.figure(figsize=(12, 6))
bars = plt.bar(chain_counts['name'], chain_counts['aggregate_rating'],
color=colors)

plt.xlabel('Restaurant Name')
plt.ylabel('Mean Aggregate Rating')
plt.title('Mean Aggregate Rating of Top 20 Restaurants')

plt.xticks(rotation=90, ha='right')
plt.tight_layout()


for bar in bars:
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height(),
             f'{bar.get_height():.2f}', ha='center', va='bottom',
fontsize=10)

plt.show()
```



Observations & Recommendations

Observations

- **Highest Average Rating: Barbeque Nation** has the highest average rating among the top 20 restaurant chains.

- **Lowest Average Rating:** ** Monginis** has the lowest average rating.

Recommendations

1. **Highlight High-Rated Chains:** Zomato can **promote top-rated chains** like **Barbeque Nation** to attract more customers and boost sales.

2. **Identify Areas for Improvement:** Analyze **customer feedback and ratings** for lower-rated chains like **Monginis** to identify weaknesses and suggest corrective actions.

3. **Partner with Top Chains:** Collaborate with **high-rated restaurant chains** to offer **exclusive deals and promotions** to enhance customer engagement.

Restaurant Features

Identify and Extract Specific Features :

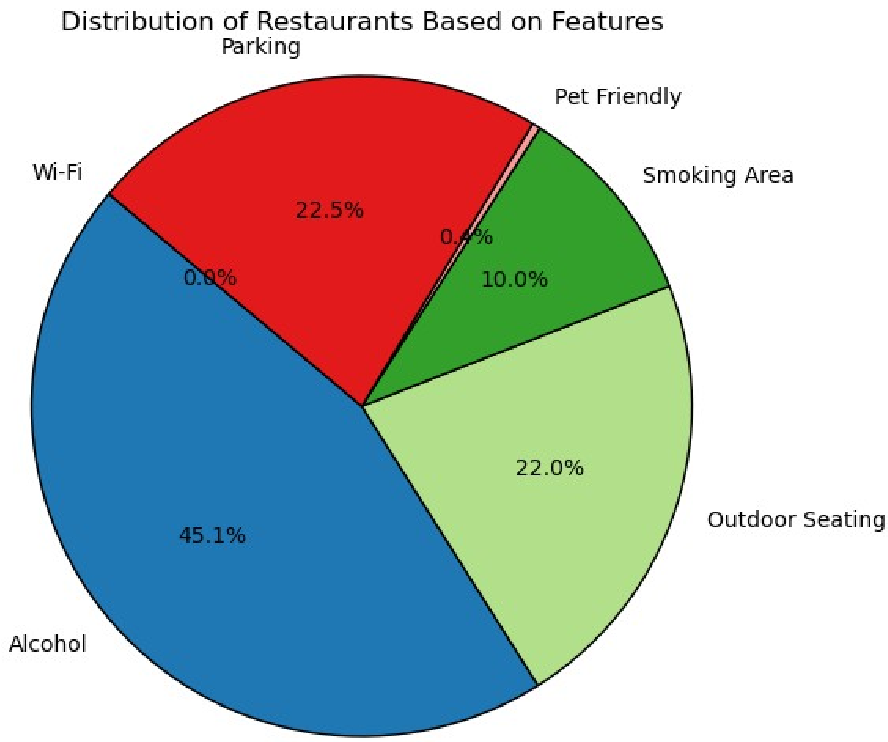
```
# Define a list of features to check for in the 'highlights' column
features = ['Wi-Fi', 'Alcohol', 'Outdoor Seating', 'Smoking Area',
'Pet Friendly', 'Parking']

for feature in features:
    df1[feature] = df1['highlights'].apply(lambda x: 1 if feature in x
else 0)

(df1[features].head(10))
```

```
   Wi-Fi  Alcohol  Outdoor Seating  Smoking Area  Pet Friendly
Parking
0      0        0                0             0             0
0
1      0        1                0             0             0
0
2      0        1                1             0             0
0
3      0        0                0             1             0
0
4      0        1                1             1             0
0
5      0        1                0             0             0
1
6      0        0                0             0             0
0
7      0        1                0             0             0
0
8      0        0                0             0             0
0
```

```
9       0         1                 1             0             0
0
```

Distribution of Restaurants Features Based

```
feature_counts = df1[features].sum()

plt.figure(figsize=(10, 6))
plt.pie(feature_counts, labels=feature_counts.index, autopct='%1.1f%
%',
        colors=plt.cm.Paired.colors, startangle=140,
wedgeprops={'edgecolor': 'black'})

plt.title('Distribution of Restaurants Based on Features')
plt.axis('equal')  # Ensures the pie chart is circular
plt.show()
```



Observations & Recommendations

Observations

- **Most Common Feature: Alcohol** is the most common feature among restaurants.

- **Least Common Features: Pet-Friendly** and **Smoking Area** are the least common features.

Recommendations

1. **Highlight Popular Features:** Promote restaurants that offer **Wi-Fi** and **alcohol availability** to attract more customers.

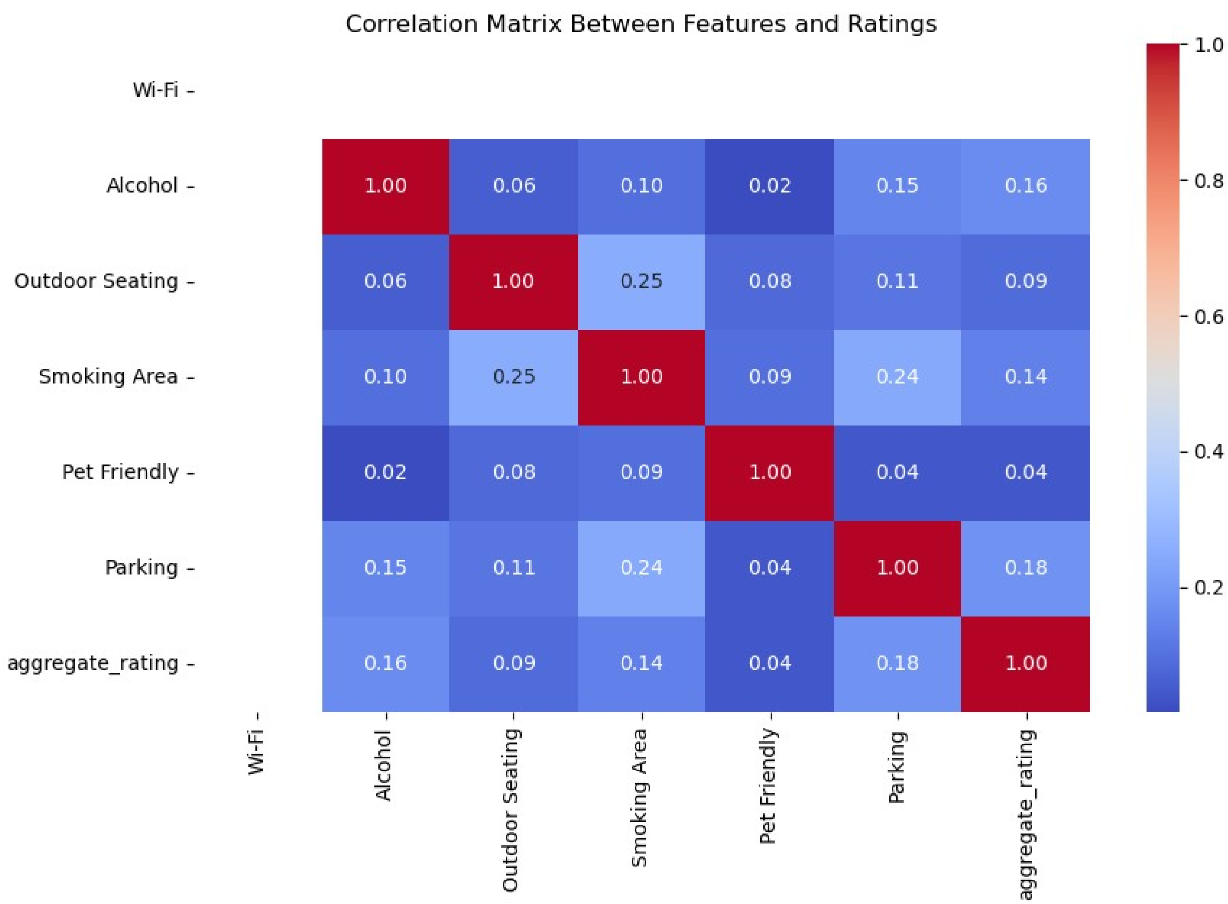
2. **Target Specific Segments:** Cater to niche customer groups by highlighting restaurants with **pet-friendly spaces** or **outdoor seating**.

3. **Partner with Venues:** Collaborate with venues that provide unique features like **smoking areas** or **dedicated parking** to expand customer reach.

Correlation Between Features and Ratings :

```
correlation_data = df1[features + ['aggregate_rating']]
correlation_matrix = correlation_data.corr()

print(correlation_matrix)

plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='.2f')
plt.title('Correlation Matrix Between Features and Ratings')
plt.show()
```

```
                  Wi-Fi   Alcohol  Outdoor Seating  Smoking Area  \
Wi-Fi               NaN       NaN              NaN           NaN
Alcohol             NaN  1.000000         0.055327      0.096192
Outdoor Seating     NaN  0.055327         1.000000      0.253829
Smoking Area        NaN  0.096192         0.253829      1.000000
Pet Friendly        NaN  0.015834         0.084368      0.094067
Parking             NaN  0.149183         0.110840      0.244973
aggregate_rating    NaN  0.163742         0.086409      0.135202

                  Pet Friendly   Parking  aggregate_rating
Wi-Fi                      NaN       NaN               NaN
Alcohol               0.015834  0.149183          0.163742
Outdoor Seating       0.084368  0.110840          0.086409
Smoking Area          0.094067  0.244973          0.135202
Pet Friendly          1.000000  0.042639          0.039264
Parking               0.042639  1.000000          0.179302
aggregate_rating      0.039264  0.179302          1.000000
```



Observations

1. **Weak Correlation Between Features and Ratings**
   - The correlation between restaurant features (Wi-Fi, Alcohol, Parking, etc.) and aggregate ratings is generally weak, with values mostly below 0.2.
2. **Parking Shows the Highest Correlation with Ratings (0.18)**
   - Restaurants with parking facilities tend to have slightly higher ratings, suggesting that accessibility is an important factor for customers.
3. **Alcohol Service Has a Slight Positive Impact on Ratings (0.16)**
   - Restaurants serving alcohol show a small positive correlation with higher ratings, indicating that it may contribute to a better dining experience.
4. **Smoking Area and Outdoor Seating Have Minimal Impact**
   - Both features show low correlation with ratings, implying they are not significant determinants of customer satisfaction.
5. **Pet-Friendly Restaurants Have the Lowest Correlation with Ratings (0.04)**
   - Pet-friendly policies do not significantly affect ratings, possibly because they cater to a niche audience.

Recommendations

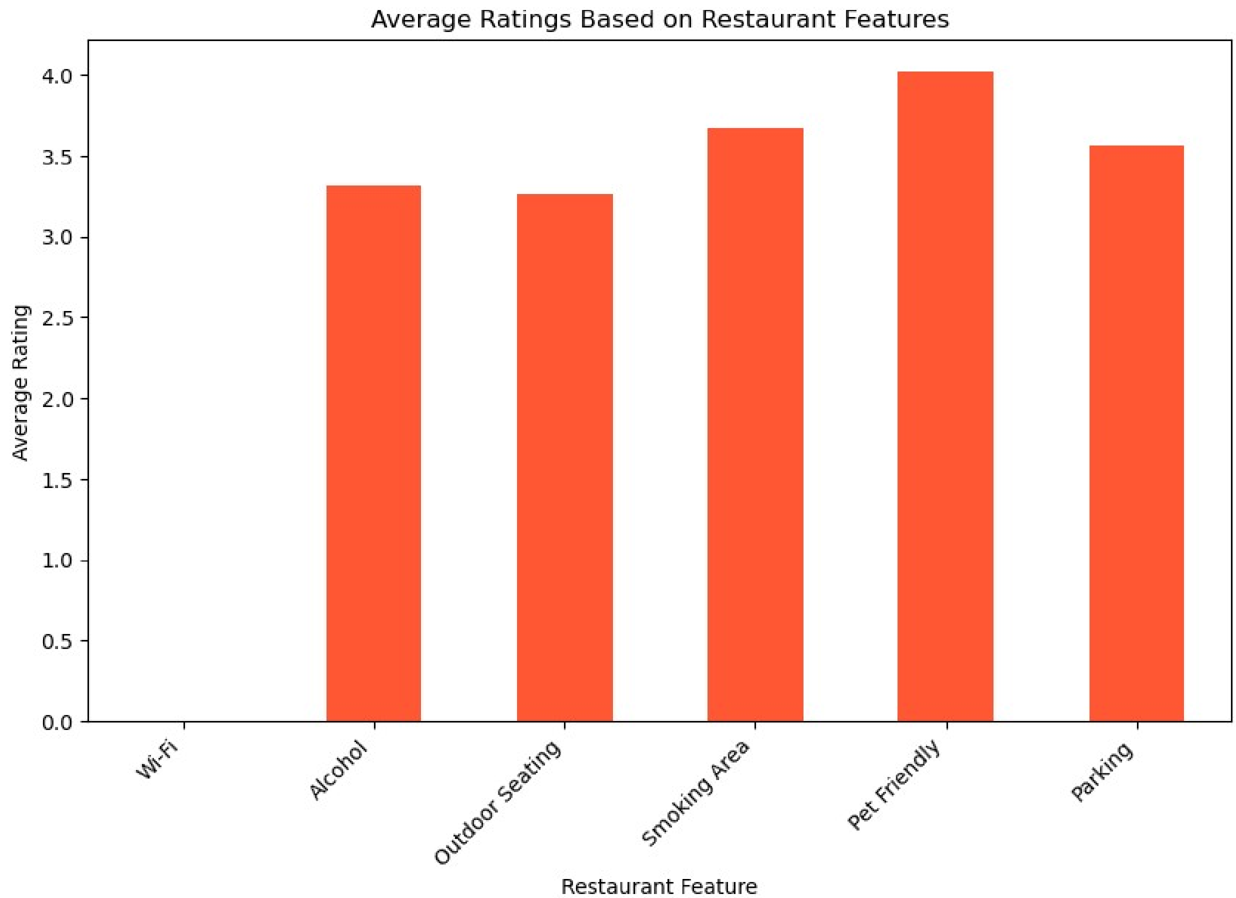
1. **Enhance Parking Facilities**

- Since parking availability has the highest correlation with ratings, restaurants should invest in improving or ensuring parking access for customers.

2. **Consider Alcohol Service Where Possible**
   - Restaurants that are legally allowed to serve alcohol may benefit from adding it to their offerings, as it slightly contributes to higher ratings.
3. **Focus on Other Service Improvements**
   - Since features like Wi-Fi, smoking areas, and pet-friendly policies have minimal impact on ratings, restaurants should focus on food quality, service, and ambiance for better customer satisfaction.
4. **Re-Evaluate the Importance of Outdoor and Smoking Areas**
   - These features have low correlation with ratings, so restaurants should assess their target audience before prioritizing investments in them.

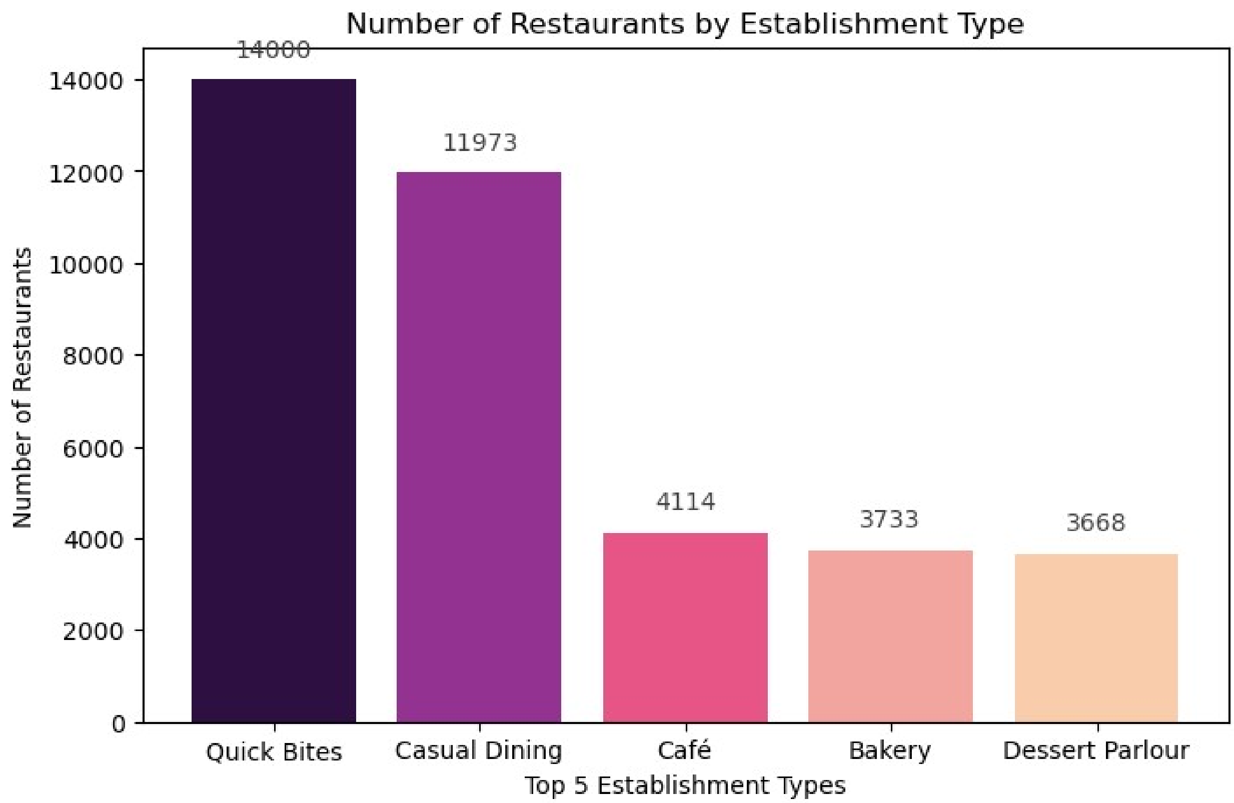
Distribution of Restaurants Based on Features :

```
feature_ratings = {}
for feature in features:
    avg_rating = df1[df1[feature] == 1]['aggregate_rating'].mean()
    feature_ratings[feature] = avg_rating

feature_ratings_series = pd.Series(feature_ratings)

plt.figure(figsize=(10, 6))
feature_ratings_series.plot(kind='bar', color='#FF5733')  # Changed
color to orange
plt.title('Average Ratings Based on Restaurant Features')
plt.xlabel('Restaurant Feature')
plt.ylabel('Average Rating')
plt.xticks(rotation=45, ha='right')
plt.show()
```



Number of restaurants by establishment type

```
est_count = df1.groupby("establishment")
["res_id"].count().sort_values(ascending=False).head(5)

colors = ["#2d0f41", "#933291", "#e65586", "#f2a49f", "#f9cdac"]

plt.figure(figsize=(8, 5))
plt.bar(est_count.index, est_count.values, color=colors)

plt.xlabel("Top 5 Establishment Types")
plt.ylabel("Number of Restaurants")
plt.title("Number of Restaurants by Establishment Type")

for i, v in enumerate(est_count):
    plt.text(i, v + 500, str(v), ha="center", color="#424242")

plt.show()
```



Observations

1. **"Quick Bites" is the Most Common Establishment Type**
   - It has the highest number of restaurants (14,000), suggesting that fast-service eateries dominate the market.
2. **Casual Dining is the Second Most Popular Choice**
   - With approximately 11,973 restaurants, casual dining remains a strong contender, indicating that customers still prefer sit-down meals.
3. **Cafés, Bakeries, and Dessert Parlours Have a Smaller Presence**
   - Cafés (4,114), Bakeries (3,733), and Dessert Parlours (3,668) have significantly fewer outlets, suggesting they cater to niche audiences.
4. **Sharp Drop in Establishments Beyond Quick Bites & Casual Dining**
   - There is a steep decline in numbers after the top two categories, highlighting a possible market saturation in fast food and sit-down dining.

Recommendations

1. **Invest in "Quick Bites" for High Demand**
   - If opening a new restaurant, consider a fast-service model as it dominates the market.
2. **Casual Dining as a Premium Option**
   - While not as numerous as Quick Bites, Casual Dining is still a strong segment and could be profitable with unique offerings.
3. **Opportunities in Cafés and Dessert Parlours**

    - The lower numbers indicate potential for new players, particularly in underserved areas or with innovative concepts.
4. **Market Research Before Opening a New Establishment**
    - Since the restaurant industry is highly competitive, conducting a location-based analysis can help determine the best establishment type for success.

Restaurants Based On Highlights

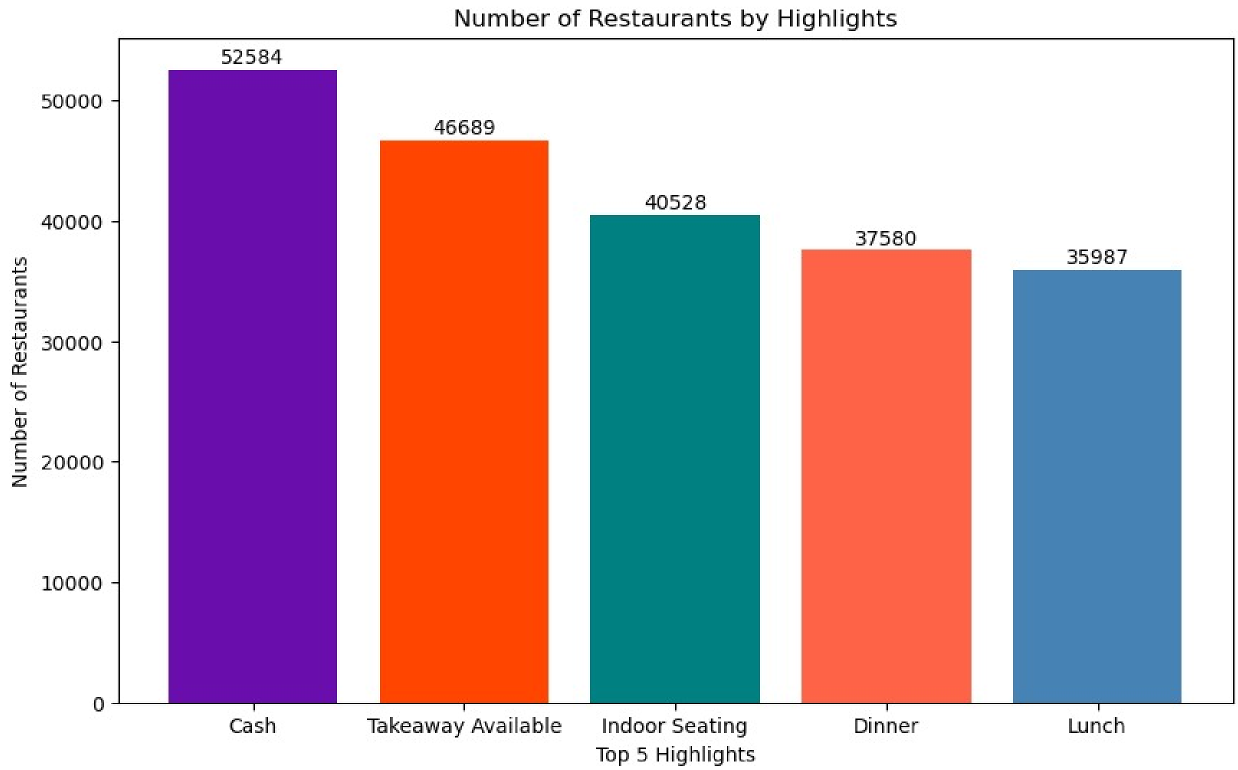
```
df1["highlights"][0]
```

```
"['Lunch', 'Takeaway Available', 'Credit Card', 'Dinner', 'Cash', 'Air Conditioned', 'Indoor Seating', 'Pure Veg']"
```

```
hl = []
df1["highlights"].apply(lambda x : hl.extend(x[2:-2].split("', '")))
hl = pd.Series(hl)
print("Total number of unique highlights = ", hl.nunique())
```

```
Total number of unique highlights =  104
```

```
h_count = hl.value_counts().head(5)

plt.figure(figsize=(10, 6))

colors = ['#6a0dad', '#ff4500', '#008080', '#ff6347', '#4682b4']

plt.bar(h_count.index, h_count.values, color=colors)

plt.xlabel("Top 5 Highlights")
plt.ylabel("Number of Restaurants")
plt.title("Number of Restaurants by Highlights")

for i, v in enumerate(h_count):
    plt.text(i, v + 500, str(v), ha='center', color='black')

plt.show()
```



Observations

1. **Cash Payment is the Most Common Highlight**
   – The majority of restaurants accept cash, making it the most common highlight.
2. **Takeaway is Highly Available**
   – A significant number of restaurants provide takeaway services, indicating a strong preference for convenience.
3. **Indoor Seating is a Popular Feature**
   – Many restaurants offer indoor seating, suggesting that dine-in experiences are widely available.
4. **Dinner is More Popular than Lunch**
   – More restaurants are open for dinner compared to lunch, indicating a higher focus on evening dining.

Recommendations

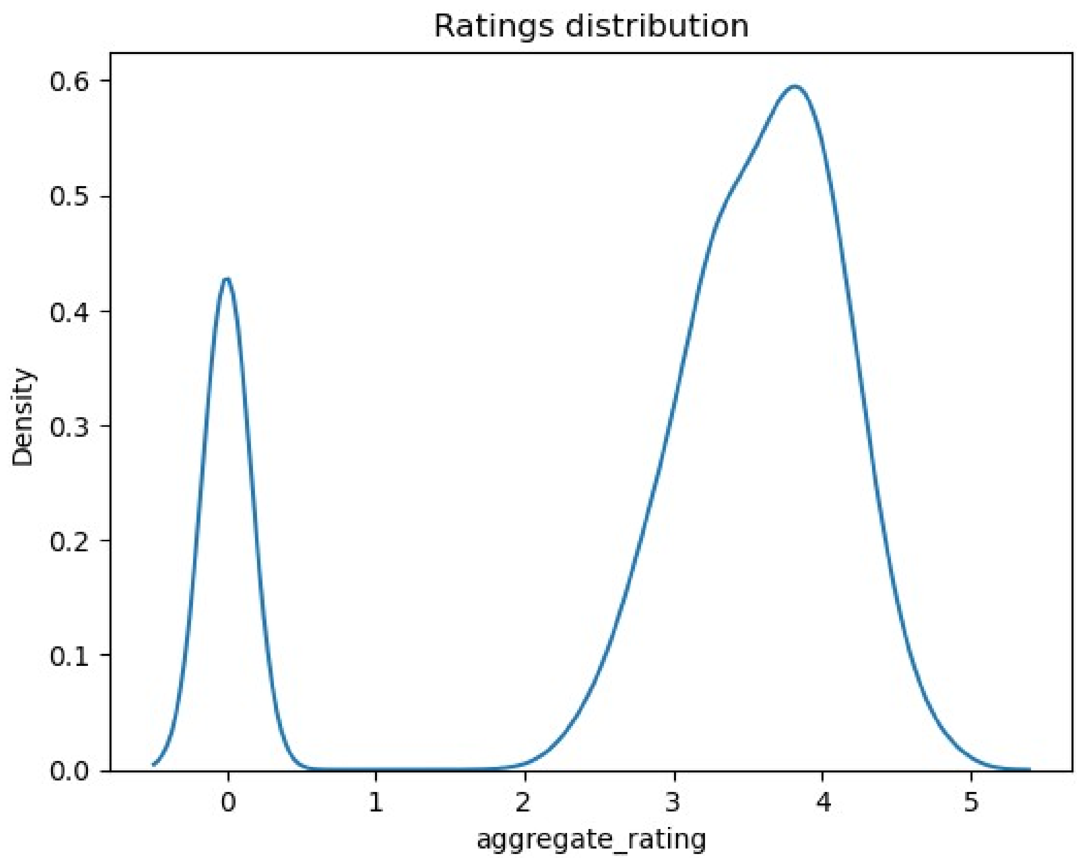
1. **Leverage Cash Acceptance**
   – Since cash is widely accepted, ensure smooth payment processes and possibly introduce digital payment options to cater to changing trends.
2. **Enhance Takeaway Services**
   – Restaurants should focus on optimizing takeaway services, such as packaging and delivery speed, to attract more customers.
3. **Improve Indoor Dining Experience**
   – Investing in better ambiance, comfort, and hygiene in indoor seating areas can enhance customer satisfaction.

4. **Expand Lunch Offerings**
   - Restaurants can introduce lunch promotions or business lunch specials to attract more midday customers.

Word Cloud for Reviews

First Let's see how the ratings are distributes :

```
sns.kdeplot(df1['aggregate_rating'])
plt.title("Ratings distribution")
plt.show()
```



Observations

1. **Bimodal Distribution of Restaurant Ratings**
   - The ratings show two peaks, one around **0.5** and another around **4**.
   - This suggests that a significant number of restaurants either have **very low ratings** or **very high ratings**, with fewer in the middle range.

Recommendations

1. **Focus on High-Rated Restaurants**

- Prioritize marketing and promotions for restaurants with **ratings of 4 and above** to attract more customers.

- Highlight positive reviews and customer testimonials in promotional campaigns.

2. **Address Low-Rated Restaurants**
   - Investigate the factors contributing to **low ratings (1.5 range)** and implement necessary improvements.

   - Enhance service quality, improve food standards, and refine the overall customer experience.
3. **Customer Feedback Analysis**
   - Regularly analyze customer **reviews and feedback** to identify common complaints and trends.

   - Implement corrective measures based on data-driven insights to **increase customer satisfaction**.

```
df1['rating_text'].value_counts()
```

```
rating_text
Average         16256
Good            16006
Very Good       10901
Not rated        9662
Excellent        1609
Poor              575
Sangat Baik         9
Çok iyi             8
Bom                 7
Muito Bom           5
İyi                 5
Baik                5
Velmi dobré         5
Buono               4
Dobré               4
Promedio            4
Skvělá volba        4
Průměr              4
Excelente           3
Muy Bueno           3
Skvělé              3
Vynikajúce          2
Terbaik             2
Veľmi dobré         2
Bardzo dobrze       2
Muito bom           1
Ortalama            1
Scarso              1
Bueno               1
```

```
Harika                   1
Eccellente               1
Média                    1
Dobrze                   1
Name: count, dtype: int64
```

Replace specific rating texts

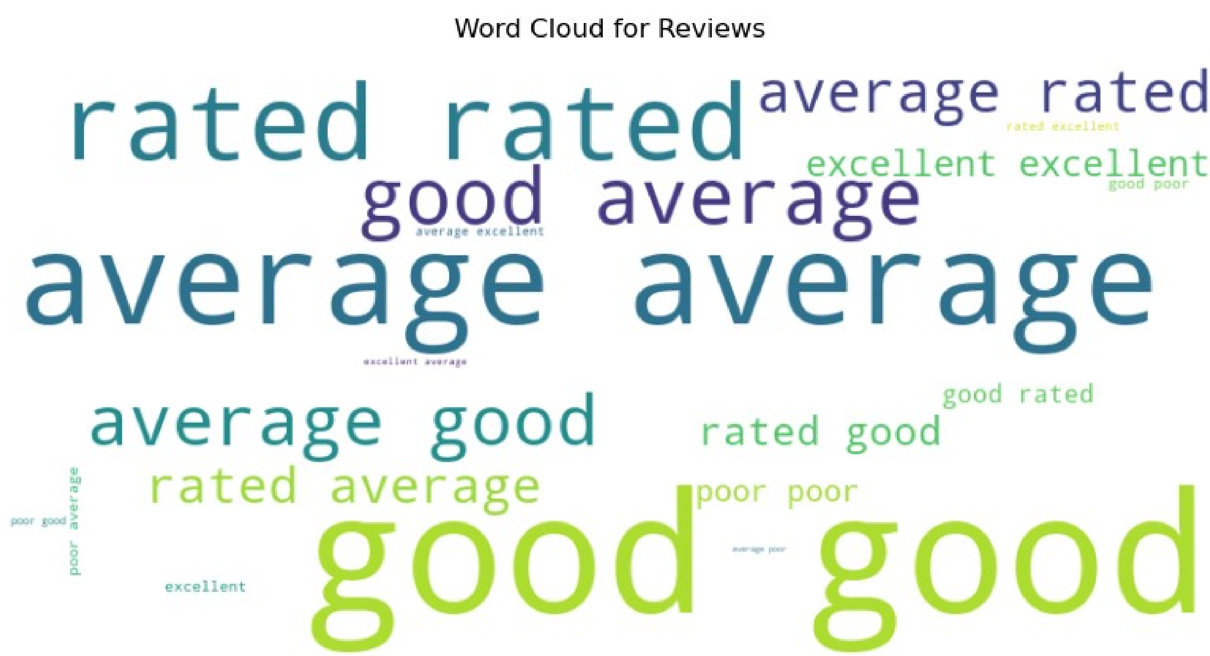
```
df1['rating_text']=df1['rating_text'].replace({'Çok iyi' : 'Good',
'Sangat Baik' : 'Average', 'Muito Bom' : 'Very Good',
                                             'Excelente' :
'Excellent', 'Muy Bueno' : 'Excellent' ,'Excelente' : 'Excellent',
'Muy Bueno' : 'Poor',
                                             'Bardzo dobrze' : 'Good',
'Bom' : 'Average' , 'Baik': 'Excellent', 'Skvělé' : 'Not rated','Velmi
dobré' : 'Not rated',
                                             'Buono' : 'Excellent',
'Dobrze' : 'Poor', 'Wybitnie' : 'Not rated', 'Eccellente' : 'Very
Good' , 'Vynikajúce' : 'Average',
                                             'Průměr' : 'Poor',
'Média' : 'Good','Promedio':'Not rated','Muito bom' :
'Excellent','Ortalama': 'Poor', 'Średnio' : 'Good',
                                             'Priemer' :
'Good','Media' : 'Average','Biasa' : 'Excellent','Scarso':
'Poor','İyi' : 'Excellent', 'Harika' : 'Very Good',
                                             'Ottimo' :
'Average','Veľmi dobré': 'Excellent','Terbaik' : 'Excellent', 'Skvělá
volba' : 'Good', 'Dobré' : 'Very Good',
                                             'Bueno' : 'Good'})
df1['rating_text'].value_counts()
```

```
rating_text
Average      16274
Good         16022
Very Good    10912
Not rated     9674
Excellent     1631
Poor           585
Name: count, dtype: int64
```

First install Wordcloud

```
pip install wordcloud

import string
from nltk.corpus import stopwords
from wordcloud import WordCloud
import matplotlib.pyplot as plt
```

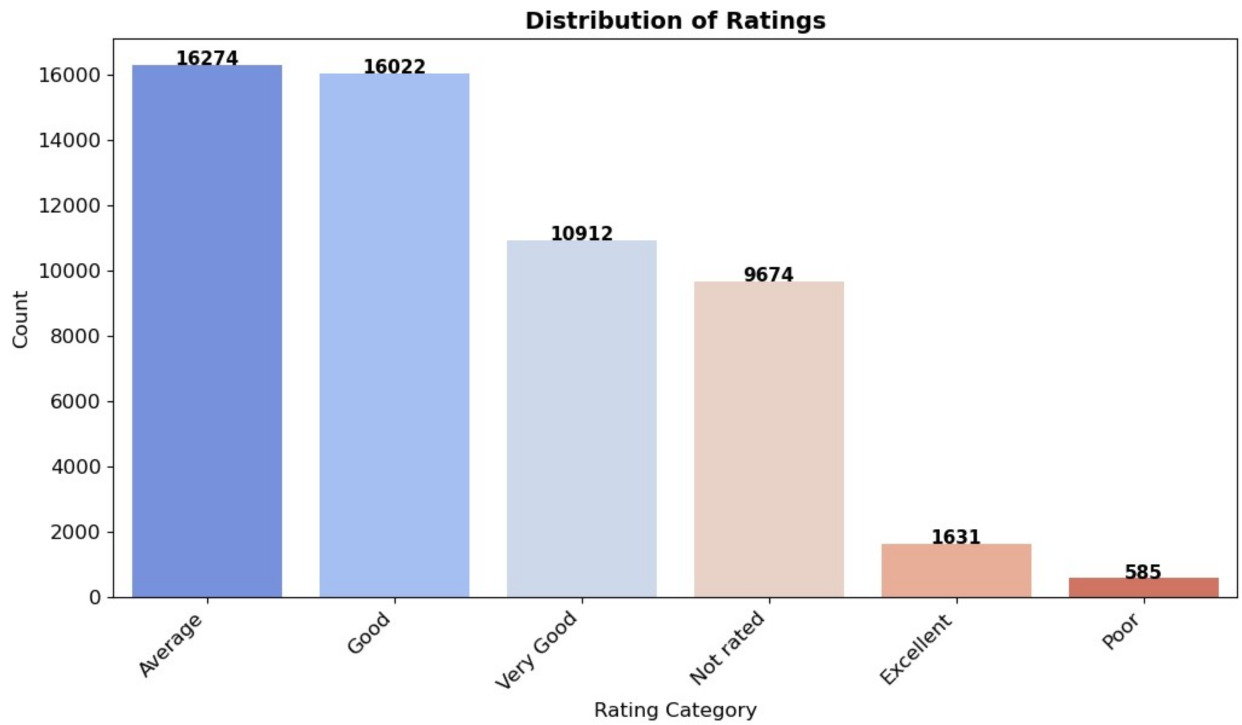
```python
reviews = df1['rating_text']

def clean_text(text):
    text = text.translate(str.maketrans("", "", string.punctuation))
    text = text.lower()
    stop_words = set(stopwords.words('english'))
    text = ' '.join([word for word in text.split() if word not in
stop_words])
    return text

cleaned_reviews = reviews.apply(clean_text)

all_reviews = ' '.join(cleaned_reviews)

# Generate a Word Cloud
wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(all_reviews)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Reviews')
plt.show()
```



Plotting rating text

```python
high = df1['rating_text'].value_counts()
colors = sns.color_palette("coolwarm", len(high))
```

```
plt.figure(figsize=(12, 6))
g = sns.barplot(x=high.index, y=high.values, palette=colors)

plt.xticks(rotation=45, ha='right', fontsize=12)
plt.yticks(fontsize=12)
plt.title("Distribution of Ratings", fontsize=14, fontweight='bold')
plt.xlabel("Rating Category", fontsize=12)
plt.ylabel("Count", fontsize=12)

for index, value in enumerate(high.values):
    plt.text(index, value + 0.5, str(value), ha='center', fontsize=11,
fontweight='bold')

plt.show()
```



Observations: Most customers have rated the restaurants as "Good" or "Average". A considerable number of customers have not left any ratings. Recommendations: Increase Customer Feedback Adopt strategies to encourage more customers to provide ratings and reviews. Provide incentives like discounts or loyalty rewards to motivate feedback. Simplify the rating process to make it more accessible and easier for customers. Improve "Good" Ratings Identify opportunities to help "Good" rated restaurants achieve "Very Good" or "Excellent" ratings. Focus on improving food quality, service, and ambiance to enhance overall customer satisfaction. Address "Poor" Ratings Investigate the causes of poor ratings and identify any common issues. Take corrective measures such as enhancing service, improving cleanliness, and providing staff training. Implement a proactive strategy to reduce negative feedback moving forward.

Conclusions Based on the data analysis, we can draw the following conclusions:

1. Restaurant Chains in India Around 35% of restaurants in India are part of a chain. Domino's Pizza, Café Coffee Day, and KFC are the largest fast-food chains with the highest number of outlets. Barbecues and Grill chains receive the highest average ratings compared to other types of restaurants.
2. Popular Restaurant Categories Quick Bites and Casual Dining establishments have the most outlets. Restaurants offering alcohol tend to have the highest average ratings, votes, and photo uploads.
3. City-Wise Insights Bangalore has the largest number of restaurants. Gurgaon boasts the highest-rated restaurants, with an average rating of 3.83. Hyderabad has the highest number of critics, reflected in the most votes. Mumbai and New Delhi lead in terms of most photo uploads per outlet.
4. Cuisine Preferences North Indian cuisine is the most popular in India, followed by Chinese. International cuisines tend to receive higher ratings than local options. Gastro pubs, Romantic Dining, and Craft Beer features are highly rated by customers.
5. Pricing and Rating Trends The majority of restaurants have ratings ranging from 3 to 4. Most restaurants are budget-friendly, with the average cost for two ranging from ₹250 to ₹800. There are fewer restaurants in the higher price brackets. As the average cost for two rises, the chances of a restaurant receiving a higher rating also increase.